Thesis Title:

Essays on Capital Market Integration

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Abstract

Essays on Capital Market Integration

The thesis comprises three independent essays on capital market integration; focussing on developed financial markets in Europe and G10 industrialised nations. These essays are motivated by a comprehensive theoretical review of the current literature on capital market integration which suggests that further investigation of a number of key issues would be extremely useful. The first essay examines the dynamics of the evolving financial and economic interdependencies between three core European nations (France, Germany and UK) and thirteen other European nations. We employ measures of linear dependence and feedback developed by John Geweke (1982) – JASA, 77, 304-324 – to define periodic integration measures that capture the time varying nature of capital market integration in Europe. Evidence from the tests of capital market integration are analysed in terms of fundamental macroeconomic variables to see whether stock market integration is driven by or dependent on economic convergence. The results suggest that European capital markets are becoming integrated especially since the 1990's. Evidence is found in support of a strong relationship between our time varying integration measures and some macroeconomic variables indicating an increase in economic convergence.

The second essay analyses common asset price behaviour in G10 equity and bond market using an innovative dynamic factor modelling framework. Our methodology combines an observable and a latent variable factor structure and decomposes the total variation in the system into a number of differential effects. Generalised methods of moments (GMM) estimation technique and the Kalman filter are used to derive the decompositions and extract the unobservable factors. The results suggest that G10 equity and bond markets are broadly partitioned on regional lines. However, regional segmentation is more emphatic for the bond markets than for the equity markets

The third essay considers the issue of conditional or time-varying correlations and conditional volatility spillovers across international stock markets. It focuses specifically on conditional sectoral volatility spillovers into the UK stock market and assesses the effects of non-market-wide volatility on UK stock market volatility. The dynamics of volatility emanating from international sectoral portfolios is assessed and their effects on overall UK stock market volatility are discussed. Inter-sectoral volatility transmission between the UK, US and the European markets are also investigated. To extract the time-varying (conditional) correlations between the UK stock markets and the selected US and European sectors and, between the UK sectors and US and European sectors, we rely on both the model by Engle and Kroner (1995) and the dynamic conditional correlation (DCC) model suggested by Engle (2002). The transmission of volatility from the US and European sectors to the UK stock market is assessed in the multivariate generalised autoregressive conditional heteroscedasticity (MVGARCH) model the model of Engle and Kroner (1995). We find substantial evidence of international sectoral volatility spillover into the UK stock market.

The material contained in this thesis has not been previously submitted for a degree in this or any University.

Dedicated to my parents,
Alhaji Joe Lahai Stevens and Mrs Kadiatu Stevens

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CHAPTER ONE

INTRODUCTION

Debate about the internationalisation of national equity and bond markets continues to occupy the attention of finance and economics academics as well as practitioners. Since the early 1980's, the globalisation of the financial services sector has been in the forefront of international finance. Large and complex financial institutions have come to transcend national boundaries and now have a presence in most of the major financial centres of the world. This has led to increased consolidation in the financial services sector. Due to the enormous advancement in information technology, information flow between international financial centres has become almost instantaneous. The costs of large cross border transactions are far less than they were a decade or two ago; leading to increased pluralism in international finance. For example, anecdotal evidence suggests that there is an increase amount of deals across currencies and markets undertaken by central counter party clearing houses following the removal of barriers to cross-border trade[1]. These developments in international business finance have given rise to a growing literature on capital market integration in empirical finance.

However, accompanying the globalisation of finance is the additional burden on financial authorities who monitor international financial stability, including payment systems stability and oversight, to maintain a sound and robust international financial architecture and, international portfolio managers operating across national boundaries, which has required the development of sophisticated risk management strategies. Recent episodes of financial instability such are the collapse of Barings, the Asian financial crises, the debacle at LTCM, the Russian bond market default and the Enron corporate governance and financial reporting scandal raises very important questions about financial market interlinkages. Does the Russian crisis, for example, affects only the national markets with which they share common exposures to common macroeconomic shocks or is it specific to certain class of investors or is it market-wide? The evidence seems to suggest that these crises do propagate themselves rapidly across markets but sometimes with a differential impact; that is, affecting some markets more severely than others or being confined to a particular sector. Another interesting question is whether the propagation of shocks across international markets is the results of some lead-lag structure that exists between these markets.

A financial crisis usually leads to increased international financial market volatility because they unsettle financial markets and significant spillover of erratic market behaviour is observed, producing strong price movements in financial markets worldwide. The events surrounding the stock market crash of 1987 is a case in point. Empirical evidence, Longin and Solnik (2001) and Ang and Bekaert (2002), suggests that financial market volatility is highest during periods of falling prices or severe 'bear markets'. Falling equity prices, for example could be precipitated by a financial cries emanating from one market but spreads rapidly across international markets causing severe market turbulence. There is therefore an urgent need for even closer international cooperation between financial authorities to firstly strive to prevent crises and if not, manage these financial crises effectively when they do occur[2].

[1] A central counter party clearing house is the financial body that acts as the legal counter party to both sides in a transaction in financial markets.

[2] International financial authorities like the International Monetary Fund (IMF) and the Bank for international settlements (BIS) perform an international coordination role in the monitoring of international financial stability.

One inference that is normally gleaned from the closer interlinkages between major international financial centres' is that international equity and bond markets are integrated. However, obtaining a straightforward measurement of the extent of integration in international financial markets is problematic. Several approaches to measuring financial market integration have been suggested in the academic literature. These methodologies range from directly observing the extent of the barriers to international trade, to the comparison of national consumption pattern across countries, see for example Bayoumi and MacDonald (1995).

Researchers in financial economics have largely relied on asset pricing theories, especially international asset pricing models, to be able to measure stock market integration[3]; due perhaps to the difficulty that arises when one attempts to compare the severity of capital controls or the barriers to arbitrage across countries particularly because the mechanisms for restricting capital movement varies for most countries. Interesting examples of these differences are provided in Bekaert (1995) and Korajczyk (1996). If capital markets are integrated, the law of one price (LOP) must prevail. In other words, in a global capital market the prices of comparable securities in different markets should not be different, and the returns must be similar, if not, arbitrageurs will exploit any small discrepancy in the prices of the comparable security in different national stock markets. The LOP has motivated most the models that have been used to study financial market integration. Indicative examples are provided in Adler and Dumas (1983) and Stulz (1995b).

In this thesis a number issues that are relevant to our understanding of capital market integration are examined. Specifically, the thesis addresses the following questions. First, what do we know about the theoretical framework of international financial market linkages? Second, does the extent of lead-lag relationship between European financial markets suggest that these markets have become more integrated and does the level financial integration reflect commonality in the macroeconomic environment across these markets? Third, to what extent are international equity and bond markets driven by common shocks and country-specific or idiosyncratic effects? Fourth, to what extent does volatility spillovers from international sectoral markets affect UK stock market volatility?

Collectively, answers to these questions would contribute to our understanding of issues relating to international capital market efficiency, financial crises (and the spread of these crises), and international portfolio choice (including portfolio diversification and asset allocation decisions). The second question, for example, is crucial because of the relationship between the prevailing macroeconomic environment and financial asset prices. These are particularly important in the European context because of the move towards financial and economic integration over the last two decades. The third and the fourth question would enable us to adequately calibrate potential systemic risk factors in equity and bond markets. This would very useful to financial authorities responsible for controlling and managing financial instability.

The thesis is structured as a collection of essays on capital market integration and comprises six chapters. The current chapter is the introductory chapter which we

[3] See for example Solnik (1974, 1983); Alda and Dumas (1983); Gultikin et. al. (1989); Korajczyk

use to set the scene for the entire thesis. Chapter two reviews the theoretical framework of the major issues in the financial market integration literature. Chapter three, the first empirical chapter, looks at the economic determinants of the evolution in European stock market integration. Chapter four, the second empirical chapter, examines common asset price behaviour in international stock and bond markets. Chapter five, the final empirical chapter, analyses the correlation structure and volatility spillover in international sectoral equity markets. Chapter six provides a concluding summary and gives suggestions and outlook for future research. The next few paragraphs briefly introduces each chapter drawing attention to the motivations and key issues discussed and the contributions or research findings of each chapter.

Chapter two presents an extensive review of the literature on international portfolio choice and asset pricing. The structure of the literature review conducted here was inspired by two key pieces of review research that have been conducted in this area earlier; the papers by Adler and Dumas (1983) and Stulz (1995b). The chapter is motivated by the fact that the influential nature of these two papers requires a similar review which updates the keys issues and would be a welcome contribution. We therefore conduct a comprehensive review of the key issues in the literature as opposed to carrying out a chronological listing and discussion of relevant research papers. This addresses the question about our knowledge of the theoretical framework of international financial market integration. An understanding of this literature is vital to a total and complete awareness of the key issues in this field.

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and Viallet (1990); Harvey (1991); Ferson and Harvey (1994) and Korajczyk (1996).

The review therefore examined a number of key issues including, those relating to the study of international portfolio diversification and the correlation of international stock returns, the different International Asset Pricing Models (IAPM) that have been suggested in the literature, a review of financial econometric time series approach to modelling international capital market integration – Cointegration test, causality tests, lead/lag relationships, volatility transmission models, and financial contagion. The relationship between economic integration, stock market development and capital market integration, which were not specifically addressed in Stulz (1995b) for example; is also examined. The chapter therefore contributes to the to literature because it pulls together a number of existing and new strands in the literature by updating earlier discussions in Adler and Dumas (1983) and Stulz (1995b).

Chapter three, the first empirical essay, examines the dynamics of the evolving financial and economic interdependencies between three core European nations (France, Germany and UK) and thirteen other European nations. Financial and economic integration is almost a reality and it is therefore important to examine the evolution in the interaction between financial markets and the real economy in Europe. We employ measures of linear dependence and feedback developed by John Geweke (1982) – JASA, 77, 304-324 – to define periodic integration measures that capture the time varying nature of capital market integration. Evidence from the tests of capital market integration are analysed in terms of fundamental macroeconomic variables to assess whether stock market integration is driven by or dependent on economic convergence using a dynamic panel data (DPD) analysis.

The results suggest that European capital markets are becoming integrated especially since the 1990's. Evidence is found in support of a strong relationship between our time varying integration measures and some macroeconomic variables indicating an increase in economic convergence. The essay contributes to the literature on two fronts. Firstly, it presents a new application of the analysis of lead-lag relationships between purely European stock markets. To our knowledge, the only other research that employs Geweke (1982) measures of feedback (multivariate causality) between multiple time series is the work by Bracker, et al. (1999). The dynamic panel data analysis used in stage two of the analysis, as far as we are aware is a first, in this context. The essay also hypothesises on the likely role of speculators when financial market integration is not adequately explained by or associated with changing macroeconomic conditions. The results have policy implications for both the successful implementation of the euro and post euro and, whether European macroeconomic policy is optimal and efficient when there is greater policy coordination.

Chapter four, the second essay studies common asset price behaviour of equity and bond markets across the Group of Ten (G10) industrialised nations. Understanding the comovements in international equity and bond markets is crucial for international financial and monetary stability. Asset return covariances are key inputs in the construction of portfolios for investors wishing to diversify. It is therefore crucial to international asset allocation decisions. This chapter contributes to this debate by developing a methodology of decomposing the effects of shocks across international equity and bond markets. We unlock the dynamic relationship between international equity and bond markets and assess the extent of spillovers or contagion between these markets in a restricted dynamic factor modelling framework. Our methodology combines an observable and a latent variable factor structure. Instead of focussing entirely on the loadings, we decompose the total variation in the system into a number of differential effects. The model is estimated in two stages. In stage one, an observable factor model is estimated for each country. This model captures the variation in well-known risk factors that drive some part of the variance of financial returns. In stage two, a restricted unobservable factor model is fitted for the residuals from the model estimated in stage one. The model in stage two is estimated by the generalised methods of moments (GMM) technique. The Kalman Filter is used to extract the unobservable factors. The extracted residuals from the model estimated in stage two are used make inferences about the extent of capital market integration in the G10 equity and government bond markets. Specifically, we test whether the correlation matrix of the extracted idiosyncratic factors is diagonal. We also test the significance of individual bilateral correlation.

The methodology builds on existing factor models found in the literature. For example, Diebold and Nerlove (1989), Fama and French (1993), King, Sentana and Wadhwani (1994), Lin, Engle and Ito (1994), Dungey (1999) and, Dungey, Martin, and Pagan. (2000). Most of the academic research in the aftermath of the stock market crash of October 1987 suggested that economic agents did not adequately decompose the effects of economic news or information emanating from overseas. The approach we propose addresses this point through the various decompositions that we suggest. The methodology would be very useful for those involved in financial stability monitoring.

In the final empirical chapter, chapter five, we contribute to the idiosyncratic volatility debate introduced in Campbell, et al. (2001) and Schwert (2002). Recent financial market behaviour have been characterised by wide swings in financial asset prices. This chapter investigates whether international sectoral volatility, affects UK stock market volatility and to what extent does this happen. Selected US and European sectors are analysed. It focuses specifically on conditional sectoral volatility spillovers into the UK stock market and assesses the effects of non-market-wide volatility on UK stock market volatility. We also analyse inter-sectoral volatilities between the UK, US and the European block. The question of idiosyncratic volatility or non-market-wide volatility is increasingly being considered as an explanation of the increasingly high stock market volatility that has been observed recently. Campbell, et al. (2001) have shown that between 1962 and 1997 there was a noticeable increase in firm-level volatility relative to market volatility. Although aggregate stock markets volatility has tended to return to a long-run average level, firm-level volatility has not.

Chapter five considers the issue of conditional or time-varying correlations and conditional volatility spillovers across international stock markets. To extract the time-varying (conditional) correlations between the UK stock markets and the selected US and European sectors and, between the UK sectors and US and European sectors, we rely on both the model by Engle and Kroner (1995) and the dynamic conditional correlation (DCC) model suggested by Engle (2002). The transmission of volatility from the US and European sectors to the UK stock market is assessed in the multivariate generalised autoregressive conditional heteroscedasticity (MVGARCH) model; the model of Engle and Kroner (1995). Our contribution to the literature is to provide new evidence on the dynamics of volatility across stock markets from a simple sectoral market analysis. The results indicate that although a number of volatility transmission mechanisms were establish, the US pharmaceuticals sector and the European IT hardware sectors seemed to have transmitted the most volatility into the UK stock market over the sample period.

An important by product of the chapter five is the production of a simplified primer on exponentially weighted moving volatility (EWMA) estimation (Appendix 5.x). EWMA volatility and correlations are a special class of conditional volatilities and correlations. The primer discusses the EWMA methodology and offers suggestion for simple estimation of conditional correlations and volatility without requiring sophisticated financial econometric applications.

Chapter six is the concluding chapter of the thesis. It pulls together the key findings from the various empirical chapters and discusses the issues of capital market integration in a general framework. More importantly, it highlights the contributions of the thesis in terms of the extensive literature review conducted in chapter 2. The chapter also discuses policy implications of the empirical findings of the chapter and provides suggestions for directions of future research in this area.

CHAPTER TWO

THE THEORETICAL FRAMEWORK

2.1 INTRODUCTION

This chapter develops the theoretical foundations of the thesis. It reviews the relevant literature on capital market integration and related issues. As opposed to a chronological listing and discussion of the major papers, the various strands in the literature and the evolving issues are discussed and critically analysed. A formal definition of capital market integration is given in the next section. Section 3 outlines the various strands in the literature and presents a review of the key issues. Section 4 discusses the relationships between economic integration and stock market integration and stock market development. A conclusion is provided in section 5.

2.2 DEFINITIONS OF STOCK MARKET INTEGRATION

Capital markets are regarded as integrated if the reward investors receive for an investment made in securities with similar risk structures is the same in every market. In integrated stock markets, assets with the same risk or identical risk characteristics must command identical returns irrespective of which market they are quoted in. In other words, the law of one price must hold for all securities. Chen and Knez (1995) for example, suggested that, "two markets cannot be integrated in any sense if it is possible to construct two portfolios, one from each market, that have identical payoffs but different prices".

An alternative way of viewing stock market integration is to look at the extent to which foreign financial asset (shares or bonds, for example) ownership in national stock markets is regulated. However, the existence of barriers to international investments is difficult to measure. There are for example, different types of legal restrictions or taxes levied on foreign share ownership by national governments. As Campbell and Hamao (1992) noted: *legal barriers and taxes are often circumvented and also a limited number of cross-border trading might be sufficient to bring asset prices into line across markets.*

Due to the difficulties of a direct inter-country comparison of the severity of capital controls, financial economists have largely relied on asset pricing theories to measure international stock market integration[4]. Both discrete and continuous time asset pricing models have been employed[5]. This approach is, however, fraught with the same problems encountered in the domestic asset pricing scenario[6]. An assessment of the correlation structure of national consumption rates and international stock returns, but mainly international stock returns, was also regarded as a way of measuring capital market integration[7]. A low correlation between stock returns or consumption rates would indicate market segmentation. This is based on the idea that integrated markets should generally move in a synchronised fashion – which is, a perfectly plausible idea provided this synchronised behaviour could be proved empirically using robust methodologies[8] and explained by sound economic theory. Although this method has been criticised

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[4] See for example Solnik (1974b), Korajczyk and Viallet (1989) and Harvey (1991). More detail is provided in the next section

[5] These asset pricing models have either been equilibrium or non-equilibrium-type models such as the standard multifactor models. These models are introduced in the next sub-section.

[6] The problems of domestic asset pricing models include the misspecification of the market portfolio as reported in Fama and French (1992). Other problems include the implicit assumption of market efficiency and in the case of the international version, market integration. These issue are discussed in the next section

[7] Levy and Sarnat (1970) was one of the first studies to use the correlation structure of international investments to measure capital market integration

[8] This issue is actually one the motivations of the empirical work done in chapters 4 & 5.

severely[9] it was, nevertheless, the primary 'modus operandi' for the assessment of the potential benefits of holding internationally diversified portfolios. In fact, and perhaps more importantly, it must be noted that the literature on capital market integration has its roots in discussions about potential gains from international portfolio diversification, an active debate in the portfolio theory literature.

Alternative methods of measuring international capital market integration have also evolved out of the econometric time series literature. For example the causal relationships between financial times series in the Granger (1969) and Sims (1972) sense and, cointegration methods developed by Engle and Granger (1987) have been used to measure capital market integration[10]. It also included ideas from the wider Vector Autoregression (VAR) literature especially innovation accounting methods – impulse response functions and variance decompositions[11]. Furthermore, the nature of volatility as described by Engle (1982) and Bollerslev (1986) has been used to examine volatility clustering and transmission across international stock market[12]. Others have also looked at the volatility transmission and financial contagion problem from a signal extraction standpoint using the Kalman Filter[13].

Integrated capital markets can therefore be described either from the point of view of the return generating process of a security if this process is characterised by an international asset pricing or multifactor model or; from the time series patterns of

[9] By Adler and Dumas (1983) for example.
[10] For example Taylor and Tonks (1989) and, Clare, et al. (1995). More details is given in the next section
[11] Eun and Shim (1989) and Phylaktis (1999) used a VAR system and impulse response analysis to study the integration of stock markets
[12] For example, Hamao, et al. (1990), Koutmos and Booth (1995), Koutmos (1996) and, Karolyi (1995). See section 2.4 for more details.
[13] See for example Lin, et al. (1994)

international or multi-country stock returns series measured by the causal characteristics of the returns or their volatilities. These issues are looked at in extensive detail in the next section.

2.3 Literature Survey: key issues

Key issues in the capital market integration literature can be viewed from those relating to international portfolio choice and international asset pricing. So far, two outstanding reviews of these issues have been provided by Adler and Dumas (1983) and Stulz (1995b)[14]. These two reviews are very self-contained and covered some of the most important theoretical and empirical issues in the international portfolio diversification and international asset pricing literature. In this chapter, we adopt a similar structure and present a more extensive and up-to-date review. This chapter will examine the following key issues:

(a) Issues relating to the study of international portfolio diversification and the correlation of international stock returns.

(b) International Asset Pricing Models

    a. The international Capital Asset Pricing Model (ICAPM) – also known as the international Asset Pricing Model (IAPM)

    b. The international Arbitrage Pricing Theory (IAPT)

    c. The International Consumption CAPM (ICCAPM)

    d. Other single factor and multifactor models of international capital market integration including the Time Varying World Market integration model

[14] Shawky, et al. (1997) also provided a review of some of the key empirical issues.

(c) Financial econometric time series approach to modelling international capital market integration – Cointegration test, causality tests, lead/lag relationships, volatility transmission models, and financial contagion.

(d) The relationship between economic integration, stock market development and capital market integration

2.3.1 International Portfolio Diversification

This sub-section reviews the major issues in the international portfolio diversification literature. The international applications of portfolio theory and the potential gains of international diversification are discussed. We then address the effects of currency fluctuations in international investments, the merits of industrial diversification and, the correlation structure of international stock markets, which is considered a major determinant of international diversification. A synthesis of the 'home bias puzzle' is then conducted and we conclude with a discussion of the widely observed barriers to international investments and describe how the cross-listing of securities in international stock markets decreases the severity of the barriers to international investments and maximises the gains of international diversification for both the cross-listing firm and the investors in the cross-listed market.

The basic logic of portfolio theory and portfolio diversification is due to Markowitz (1952, (1959) and later Markowitz (1991a, b). This logic is predicated on the fact that investors have to make investment decisions under conditions of uncertainties or risk. Decisions have to be taken on the basis of probabilities. A probability (distribution) under these conditions is explained by: the expected value of the returns on investment, the variance or standard deviations of the returns, and the correlation between returns[15]. These are the most important factors that should be considered. Under portfolio theory, we combine asset in a portfolio in order to maximise returns and minimise risk (variance or standard deviation). To achieve effective diversification we select or combine assets on the basis of the correlation coefficient between the assets. The correlation coefficient ranges between –1 and

+1. Since the introduction of portfolio theory, there has been significant theoretical extensions of the theory and tremendous empirical research have taken place[16]. In fact, portfolio theory is generally considered to be the foundation of modern finance. This research has been conducted in both the domestic and international settings. For our purposes, we shall focus on the international extensions of portfolio theory.

Grubel (1968) was the first to extend Harry Markowitz's seminal work to international stock markets[17]. In his analysis, Grubel developed a two-country model in which both countries are assumed to have independent macroeconomic policies and trade financial and real assets between them. The theoretical model developed is used to determine the gains from international portfolio diversification. There are two forms of this model – the static model and the dynamic model. The static model calculates expected return from investing in government bonds in the two countries as the weighted average of the return on bonds in each country. The variance of the two-country bond portfolio is the weighted variances of the individual returns plus two times the covariance between the bond returns – this is now standard in the literature. The demand for foreign bonds is determined by the available wealth of the nations, the size of risk and interest rate differentials between the two counties bond returns, the degree of correlation of returns on domestic and foreign assets and the "tastes" of the public – the risk and return preferences of the market participants. The dynamic model extends the discussion of the static model to consider continuous growth in assets

[15] Mathematical definitions of these variables are standard in the finance literature. See for example Elton and Gruber (1995) or Haugen (2001).

[16] Sharpe's (1964) Capital Asset Pricing Model (CAPM), Merton's (1974) Intertemporal CAPM and the Arbitrage Pricing Theory (APT) derived by Ross (1976) are a case in point.

values in the two countries. The level of bond flows (or investments) between the countries is determined by the growth rates and the initial stocks of foreign assets held in either country. Both models were applied to 11 industrialised countries including the US and were considered under alternative exchange rate regimes and varying levels of capital flows between the two countries. The simple conclusion from the static model was that, as Grubel puts is: "recent experience with foreign investment returns would have given rise to substantial gains in welfare to wealth holders". The dynamic model also revealed that the gains from investing in internationally diversified portfolios were high.

The determinants of international portfolio investments as suggested by Grubel (1968) remain amongst the key factors that drive decisions on international portfolio choice and asset pricing. Grubel's empirical work should therefore be considered as the foundation for empirical assessment of investments conducted in an international context.

Other major early contributions to this literature include the work by Levy and Sarnat (1970), Grubel and Fadner (1971), Solnik (1974c) and Subrahmanyam (1975). These classic studies showed that investors that hold foreign stocks reduce the variance of their portfolios without reducing the overall expected returns. Levy and Sarnat (1970) conducted a very similar analysis to Grubel (1968) but included a larger set of countries and extended the analysis into two dimensional mean return and variance/standard deviation framework introduced by Sharpe (1964) and Lintner (1965). They examined the potential gains from international

[17] Evans and Archer (1968) conducted an empirical analysis of the benefits of diversification in terms of risk reduction but purely for domestic securities in the US. They found that there were immense risk reduction benefits from portfolio diversification.

diversification by calculating expected returns and standard deviations for common stock indices in 28 countries. Using indices denominated in US dollars to adjust for changes in exchange rates, Levy and Sarnat (1970) showed that as long as correlation of returns on common stocks held in various countries were not perfect; there were substantial gains to be made from an internationally diversified portfolio despite the relatively good performance of US common stocks at the time. They also found that the most efficient frontier was the set that included common stocks of the 28 countries. Another interesting finding in this study was that the US investor only benefited from international diversification if his portfolio included countries such as Japan, South Africa and developing countries in South America and Asia[18]. According to Levy and Sarnat, the composition of an optimal international portfolio is problematic due to the fact that there were barriers to international investments and the existence of these barriers potentially creates inefficient markets. We will address the issue of barriers to international investments later on.

Recent researches have also investigated the benefits of diversifying internationally. Grauer and Hakansson (1987), for example, used a multi-period portfolio model, which uses simple probability assessment to construct and rebalance portfolio and, showed that a portfolio set that included non-US assets provides substantial benefits especially for the highly risk averse investor[19]. Bailey and Stulz (1990), examined the evidence for diversifying in pacific basin stock markets. Generally, they find that, compared to an investor who holds only the

[18] Grubel (1968) also reported that if the portfolio set only includes assets from US, Canada and Europe the gains from international diversification are not substantial

[19] This methodology was a departure from the standard mean-variance approach adopted by earlier studies such as Levy and Sarnat (1970)or Solnik and Noetzlin (1982). This approach is based on solving a reinvestment problem by maximising a specified utility function (defined on wealth) and employing a probability assessment of the past joint empirical distribution of realised returns.

S&P 500 portfolio, the investor that holds additional assets in pacific basin stock markets could reduce overall standard deviation by a third. In a very recent study Stulz (1999) have shown that with globalisation of international financial markets, the equity cost of capital decreases primarily because "globalisation reduce the discount rate investors charge" but the decrease is only marginal due to investor 'home bias[20]' and , the "agency costs which makes it harder and more expensive to raise funds becomes less important". In other words, although the globalisation of financial markets presents an increasing need to monitor management activities, this is accompanied by increasing expected cash flows for investors. Errunza and Miller (2000) documents a 42% decrease in cost of capital in American Depository Receipts (ADR's) when markets are liberalised. Bekaert and Harvey (2000) have also suggests that, the cost of capital always decreases after a capital market liberalization with the effect varying between 5 and 75 basis points. The evidence presented here demonstrates that international portfolio diversification does not only reduce the overall risk of a portfolio, but also reduces the cost of capital of international investments which represents a substantial economic benefits for firms that raise capital internationally.

An analysis of the correlation structure of international stock returns was also conducted by Grubel and Fadner (1971). They considered the following issues: the effects of different holding periods of an investment on the correlation structure of international stock returns; the correlation among pairs of identical indices; and, the proportion of the variance (risk) of returns was due to exchange rate fluctuations. The main findings were that the correlation structure of international stock returns is an increasing function of the length over which the stock is held and therefore

[20] We examine the theoretical and empirical explanation of the 'home bias' later.

gains from international diversification are probably higher over short horizons. This therefore suggests that international equity correlation changes through time. Bracker and Koch (1999) also investigated why the matrix of correlations across equity market changes over time. They find that "the correlation matrix changes substantively across both short and long time intervals". Further, Bracker and Koch specified the economic determinants of the correlation structure using selected macroeconomic variables including the world market volatility factor, which was found to be positively related to correlation[21]. They concluded that because some the macroeconomic variables across nations do not move together, this induces divergent behaviour in national stock market which is responsible for the low correlation between countries.

Grubel and Fadner (1971) indicated that there was high correlation between identical industries especially those that were involved in international trade and, that these industries were more sensitive to international business conditions. They were, however, unable to find conclusive evidence on the effects of exchange rate fluctuations on the variance of returns. Hauser, et al. (1994) also contends that the effects of exchange rate fluctuations in internationally diversified portfolios are minimal. They advised not to hedge against foreign exchange risk in emerging markets and some developed markets because when there is negative correlation between changes in stock and currency prices hedging foreign exchange risk cannot enhance the benefits from international diversification. According to the authors, the negative correlation actually produces decreased volatility.

[21] Exchange rate volatility, term structure differentials, real interest rate differentials, the world market return and a time trend were also used in this specification.

There is however strong evidence supporting the role of exchange rate risk in international portfolio diversification decisions. Solnik (1974c) showed that exchange risks do have an effect on the variability of an internationally diversified portfolio although the overall risk of such a portfolio was still smaller than the exclusively domestic portfolio. Eun and Resnick (1988) suggested that building well-diversified portfolios would not necessarily eliminate foreign exchange risk. Using an ex-ante portfolio selection strategy which controls for both the estimation and fluctuations in exchange rates by using multi-currency diversification and hedging using forward exchange contracts, they showed that under flexible exchange rate regimes, "exchange rate fluctuation is a largely non-diversifiable factor adversely affecting the performance of international portfolios". Controlling for exchange risks would substantially increase the benefits from international portfolio diversification, Eun and Resnick (1988) recommended. A similar finding was reached by Korajczyk and Viallet (1992) who, using the Arbitrage Pricing Theory (APT), showed that although, equity portfolios were related to forward exchange contracts, forward contracts have a component of their conditional mean returns that is unexplained by their relation to equity factors[22]. In fact, Kaplanis and Schaefer (1991) have shown that for bonds and equities, internationally diversified portfolios that do not hedge currency risk may be riskier than similar domestic portfolios. More recently, Adler and Jorion (1992), Dumas and Solnik (1995), Solnik (1997) and De Santis and Gerard (1998) have all provided empirical evidence suggesting that currency risks are priced in international investment models.

[22] This was based on the assumption that, ff returns on well- diversified equity portfolios explain movements in agents' intertemporal marginal rate of substitution, then the time variation in forward

De Santis, et al. (1999) examined the effects of exchange rate risks on international investment for countries that are members of the European Monetary Union (EMU). Their results revealed that, despite the creation of the European Monetary Union (EMU), EMU countries are still sensitive to currency fluctuations. They used a conditional version of the international Capital Asset Pricing Model of Adler and Dumas (1983)[23] to decompose both the EMU and non-EMU component of aggregate currency risk in the international return generating process. They found that "currency risk is a priced factor, both in its EMU and non-EMU components". However, the empirical results indicate that returns are more sensitive to the non-EMU component of aggregate currency risk – dollar, yen and the pound sterling. According to De Santis, et al. (1999) "the most relevant currency factor is linked to the US dollar" and, "currency risk and its impact on returns vary over time as a function of changes in economic conditions and the institutional environment"[24]. Current evidence therefore suggests that exchange fluctuations are crucial in international asset allocation decisions and, researchers like Bailey, et al. (1992) have suggested that with better forecast of exchange rate changes, performance of internationally diversified portfolios would be enhanced substantially[25].

In addition to Grubel and Fadner (1971), others including Solnik (1974b), Lessard (1974, (1976) and Grinold, et al. (1989) have also provided evidence in support

risk premia should be explained by the forward contract's sensitivity to the equity portfolios and the time variation in the risk premia of those portfolios.

[23] This model is discussed in greater detail in the asset pricing section of this chapter

[24] Similar conclusions were reached by De Santis, et al. (1999b)

[25] Bailey, et al. (1992) applied the formula for the optimal hedge of a portfolio in a mean-variance framework. Basically, one constructs an optimal mean-variance portfolio that is hedge for foreign exchange risks.

inter-industry diversification[26]. Grinold, et al. (1989), for example, noted that industry factors are significant determinants of asset returns and some industries are significant global factors in their global portfolio risk factor model. More recently, this issue has been investigated, in substantial detail, by Roll (1992), Heston and Rouwenhorst (1994) and Griffin and Karolyi (1998). In the main, the key questions emanating from most of these studies are, whether the industrial structure of national indices is a very important factor in determining the correlation of international stock indices and, whether industrial diversification does increases the gains from international diversification. Lessard (1974, (1976) for example found that an industry factor plays an important role in explaining national stock market volatility. By implication, this means that the industrial structure of national stock markets must be considered in international portfolio diversification or asset allocation decisions. Roll (1992) studying 24 national indices indicated that even after adjusting non-synchronous trading inter-country correlation of indices were very modest but, when computed from "industry weighted portfolios rather than raw indexes", inter-country correlations were larger. The industrial composition of national indices, according to Roll, does explain a significant proportion of the correlation between markets. He concluded that, "national stock markets reflect the idiosyncrasies of the country's industrial structure" and there were significant benefits from international portfolio diversification if international industrial structures are taken into consideration in portfolio diversification decisions. In other words, industrial diversification contributes to the gains from international portfolio diversification – a point supported by Arshanapalli, et al. (1997). Roll also advanced the view that the

[26] Adler and Dumas (1983) noted that the issues relating to industrial and intra-industry diversification were not systematically examined at that time although, as they put it, it "is of

industrial structure of national stock exchange indices is important for explaining cross-sectional return volatility differences[27].

Heston and Rouwenhorst (1994) reported completely opposite results to those found in Roll (1992) when they investigated the significance of industrial factors on the volatility and the correlation structure of national stock index returns for 12 European countries. Heston and Rouwenhorst (1994) concluded that country-specific factors are responsible for the low correlation between national stock indices and that the industrial structure of national stock markets contributes very little to explaining difference in country return volatility. According to Heston and Rouwenhorst (1994) the benefits from international diversification are substantial for "diversification across countries within an industry" than "industry diversification within a country". Arshanapalli, et al. (1997) in their study of common time-varying volatility patterns across international stock markets using industry-adjusted data suggested a slightly different strategy to the one espoused by Heston and Rouwenhorst (1994). They suggest that investors would be better of if they invested across regions and industries rather than diversify within an industry across different geographical regions because, as they put, "the industrial mix of global investment portfolios accounts for a substantial proportion of the international diversification benefits".

In a related analysis for both emerging and developed markets, Errunza (1994) suggested that international investors must select a country first rather than the security. According to Errunza, because stocks from the same country tend to move

considerable practical interest. It is perhaps reasonable to assume that this was what motivated the recent investigations the other authors mentioned in this paragraph.

together, country selection is "the most crucial aspects of in emerging markets and most developed markets". Along similar lines, Akdogan (1996) suggested a methodology for country selection in international portfolio diversification decisions. From a single index world return generating process, Akdogan calculated the fraction a country's systematic risk that captures variability in world stock markets – the contribution of a domestic capital market to the global market risk; he uses the rate of change in this fraction[28] as a measure of integration or segmentation and select countries on this basis. This is an attractive method, to say the least, but if the world index used in the model is not the 'magic portfolio' that we require – the efficient world index – then, one would envisage problems with this methodology. Akdogan reports: "some small to medium-sized European capital markets (Finland, Denmark, Spain and Italy) along with most emerging markets exhibit segmentation, and deserve a closer look by international portfolio managers".

A recent and significant contribution to the industrial diversification debate is the work by Griffin and Karolyi (1998) which uses the new Dow Jones World Stock Index database. This database covers 25 industries and has over 66 industrial classifications. Like Heston and Rouwenhorst (1994), Griffin and Karolyi (1998) reported that little of the variation in country index returns is explained by industrial classification. They also provided new evidence on the influence of country and industry – specific factors on the variation in country index returns. Griffin and Karolyi (1998) concluded that the nature of an industry or the type of

[27] Arshanapalli, et al. (1997) also supported this view; they suggested that world capital markets are also related through their second moments.
[28] According to Akdogan, a growing fraction of systematic risk compared to the benchmark index suggests that a market is becoming more integrated and a decrease in the fraction is evidence that a stock market is segmented from world stock markets. See Akdogan (1996) for details.

goods produced in the industry determines the extent of the variance in country index returns that is explained by either industry or country – specific factors[29]. The classifications ("traded-goods industries" and nontraded-goods industries)[30] used by the authors are probably correct, to a very large extent; however, the distinction between goods traded internationally and locally might be difficult to make. Industry-specific factors (the industrial structure of markets) are only significant for diversification strategies that are geared towards selecting goods in the "traded-goods industries", Griffin and Karolyi concluded.

On issues relating to the gains from international portfolio diversification; other early contributors include Agmon (1972) and Lessard (1973). Lessard (1973) used a multivariate analysis on a group of Latin American countries and found evidence in support of the gains obtainable form holding an internationally diversified portfolio. Agmon (1972) on the other hand was very critical of previous work in this area and suggested that the hypothesis of completely segmented capital market was not the only explanation of international capital market theory. Agmon considered the possibility of an integrated capital markets and suggests that the price behaviour of international stock market was consistent with the one market theory. However, He questioned the use of common stock portfolio to represent the most efficient portfolio and was very critical about the use of correlation between indices to measure potential gains from international diversification. He noted that: "each capital market has many assets, and the composite asset, as represented by

[29] The authors described two types of industries: "nontraded-goods industries", which refers to industries that do not produce goods traded internationally such as "media, heavy construction, plantations, conglomerates, and real estates and; "traded goods industries", which refers to industries that produce goods that are traded internationally such as "automobiles, computers, office equipment, pharmaceuticals and semi-conductors". They found that country factors are more important for the "nontraded-goods industries" and industry – specific factors are more important for the "traded-goods industries".
[30] Note 11 above.

the market index, does not capture all the possibilities for diversification within a local market". Weakly correlated return indices should not necessarily imply that the benefits from international diversification would be greater. Adler and Dumas (1983) have also questioned the suggestion that low correlation between stock market returns is a sign of segmentation [although, they think, analysing the correlation among national consumption rates is "prospectively, a better approach for detecting segmentation"[31]]. According to Adler and Dumas (1983), the idea of considering the correlation between stock returns is flawed because: " There are national random factors (politics etc) which affects selectively the production activity of any country. They are reflected in stock returns but there is no evidence of segmentation". They noted that even stocks within the same market might not necessarily move together because of the selective nature of random shocks. This suggestion is very important because it demonstrates that we cannot rely on only correlation between stock indices to measure capital market segmentation or integration.

Eun and Resnick (1984) questioned the accuracy of reported correlation estimates. They conducted an empirical assessment of various methods used to forecast the correlation structure of international stock returns. On the basis of the root mean squared forecast error and stochastic dominance based on the frequency of the squared forecast errors[32], Eun and Resnick suggests the use of a "National Mean Model[33]" to forecast future correlations. These models are discussed in chapter 5.

[31] We review international consumption asset pricing models in the asset pricing sub-section. The use of correlation between consumption should be based on the "empirical validity of a consumption-based asset pricing model and the existence of complete markets"[Chen and Knez (1995)].
[32] The definition of these two criteria is elaborate. Please see Eun and Resnick (1984).
[33] The "National Mean Model" uses a method of averaging in calculating intra-country and inter-country pairwise correlation. Inter-country pairwise correlation coefficient between securities from

Clare, et al. (1995) also suggested that the use of the correlation coefficient between markets as a measure of the levels of integration or segmentation of these markets might be unreliable because stock markets often diverge considerably in the short-run but may actually be well integrated over longer periods. This point was actually proven empirically by Grubel and Fadner (1971). Also, it is should be noted that the covariance between country stock indices have also been used as a measure of market linkages and is sometimes considered a more relevant measure of co-movement (at least in the sense in which correlation has been used to describe market linkages). Griffin and Karolyi (1998) for example used covariance between international industries in their study of the role of industry – specific factors in explaining the variation in country index returns.

The validity of unconditional correlation estimates in studies of international asset price comovements have been questioned for two main reasons: firstly, whether the correlations are stable over time, and secondly, whether we could rely on correlation estimates under extreme market conditions. Kaplanis (1988) and Longin and Solnik (1995) carried out correlation and covariance stability tests on international equity markets using tests suggested by either Box (1949) or Jennrich (1970). Their results indicate that correlation and covariances matrices of equity markets have been highly unstable especially in the 1980's. In this thesis we carry out both of these tests on equity and bond markets and in addition, we conduct Bartlett's modified likelihood ratio tests for the joint stability of covariance matrices as discussed in Morrison (1976, (1990), Perlman (1980) and Anderson (1984, (2003). The question of whether correlation estimates can be relied upon

two different markets was calculated as the average of all inter-country pairwise correlation between under extreme market conditions have been investigated by amongst others, Longin (1996), Danielsson and de Vries (1997), Embrechts, et al. (1997), Longin and Solnik (2001) and Frey and McNeil (2002). These studies focussed on tails of equity return distributions which capture the so-called "extreme events" using extreme value theories. The stylised facts suggest that the left tail of the equity returns is characterised by an extreme value distribution.

Not withstanding the cited limitations of correlation analysis in studies of capital markets relationship, practitioners and researchers alike have continued to analyse the correlation structure of international equity return to assess the benefits of international diversification. Speidell and Sappenfield (1992) demonstrated empirically that correlation between stock market indices of developed countries have increased considerably[34] and suggested that emerging markets are avenues for effective diversification. These findings however, must be viewed in the context of the barriers to international investments that exists in certain markets. We shall return to this issue later on.

Michaud, et al. (1996) on the other hand, provided only limited evidence in support of high or increasing correlation coefficients between international stock markets and confirmed that there are still benefits from international portfolio diversification even during periods of declining markets. However, they stressed that although the availability of additional equity markets have considerably increased the potential of maximising returns and lowering risk, this can only be

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securities from the two countries.

[34] Roll (1992) and Heston and Rouwenhorst (1994) found low correlation coefficients for intra-country stock indices. In a static sense this is evidence that the markets are segmented.

achieved through "thoughtful international equity diversification"[35]: active global investment management should for example include the use of multiple valuation models or forecasts – considering multiple factors that affects returns and the correlations between these factors. An example is "historical market anomalous factors" which can be estimated using factor analysis. Issues such as the accurate (empirically) determination of transaction cost, an effective currency hedging policy and, a well defined and efficient global asset allocation strategy were considered – by Michaud, et al. (1996) – as crucial to obtaining the benefits of an internationally diversified portfolio.

The evolving research in financial econometrics has addressed the limitations of using a simple correlation measure by considering a conditional correlation structure – computed from a bivariate time-varying volatility model[36]. Bollerslev (1990), in his study of the coherence in short-term nominal exchange rates using a multivariate generalised autoregressive conditional heteroscedasticity (MVGARCH) model, introduced the concept of constant conditional correlation. Bollerslev proposed a joint estimation of a GARCH model and conditional correlation by maximum likelihood. Subsequently, other authors have used various specifications of the GARCH-type models to compute constant conditional correlations in studies of market integration. Koutmos (1996) and Antoniou, et al. (2001) for example, have used GARCH-type models to compute conditional correlations between stock indices. Koutmos (1996) provided evidence, which shows that, simple unconditional correlations are higher than their conditional

[35] Kahn, et al. (1996) have also designed a three-step global asset allocation procedure: forecasting asset class expected return, building optimal portfolios, and testing their out-of-sample performance. Empirical applications of this procedure show that the models perform fairly well. This methodology was developed whilst the authors were at BARRA, Inc in Berkeley (California).

[36] Estimation issues relating to conditional correlations are discussed in detail when we look at volatility and volatility transmission models in section 2.4

counterparts. This suggests that, simple correlation measures probably underestimate the potential for (and gains from) international portfolio diversification. Antoniou, et al. (2001) found similar results. The constant conditional correlation structure (model) was estimated (and extended) by Engle and Kroner (1995) under special conditions (restrictions): directly imposing *positive definiteness* on the variance-covariance matrix[37]. Compared to the constant conditional correlation structure, this specification provides some efficiency gains in estimation because it ensures a positive definite conditional covariance matrix (under weak conditions) and estimates fewer parameters. Authors who have employed this methodology in tests of capital market integration include, Malliaropulos and Priestley (1999) and, Hardouvelis, et al. (1999) although, these studies did not specifically compare simple unconditional correlations to positive definite conditional correlations. In the third empirical chapter of this thesis, we use this method to study volatility transmission between major European stock markets.

Engle (2002a) have since proposed a dynamic conditional correlation (DCC) specification for MVGARCH-type models. This model is similar to earlier conditional correlation models but it is estimated in two steps: A GARCH model is estimated for each return, and, a time varying correlation is computed between the standardised residuals. According to Engle (2002a), although the DCC model is not linear, the likelihood (function) is simpler when estimation is done in two steps. The model also drops the assumption of constancy[38], guarantees positive definite covariances and can be used for an unlimited number of assets. It considers an

[37] This model generally known as the BEKK model was originally due to Baba, et al. (1989). We employ the Engle and Kroner (1995) model for our volatility tests in chapter 6

integrated process or a mean reverting specification for correlation[39]. A logical empirical application of this very new methodology to studies of market integration should perhaps consider a combination of stock markets and industries and estimate the dynamic conditional correlations between these markets. This type of study will contribute to the ongoing debate about the benefits of international portfolio diversification and the integration of capital markets. In this regard, and following the theoretical methods described in Engle and Sheppard (2001) and Engle (2002a), and applications used in Cappiello, et al. (2003)[40]. In chapter 6 we conduct tests for volatility spillovers between equity markets and sectors using different classes of multivariate volatility models including DCC-type MVGARCH models.

Another important issue in the international portfolio diversification literature is the relationship between correlation and market volatility. Stylised facts, for example Longin and Solnik (1995), suggest that there is a positive relationship between market volatility and correlation (both conditional and unconditional) – correlations between stock markets are high during highly volatile periods or in 'bear' markets. Erb, et al. (1994) found that international equity correlation in G-7 countries is determined by the coherence between business cycles between any two countries and correlations are higher during recessions than during growth periods. This evidence is very important because the correlation structure of international equity returns is a primary input in any asset allocation decisions. King, et al. (1994) reported that, conditional correlations (and covariances) between stock markets changes over time and these changes are driven mostly by "unobservable factors"

[38] Engle suggest that even if assets have constant conditional correlations, liner combinations will not.
[39] See Engle (2002a) for further discussions

although a small proportion of the covariances are driven by "observable economic variables[41]. They studied sixteen national stock markets using monthly stock returns and found that the conditional correlations between markets are highest during severely volatile periods. Similar results were reported by Longin and Solnik (1995). Again, using a dynamic volatility (GARCH-type) model they showed that conditional correlations between major stock market rise during periods of increased market volatility[42]. Solnik, et al. (1996) provide evidence that for both stocks and bonds; they find that conditional correlation between markets increases in periods of high market volatility and indicated that the international correlations for stocks and bonds did not increase in the 1990's.

Ramchand and Susmel (1998b) used a variance regime change framework to test if market correlations changes across variance states[43]. Using weekly data on seventeen stock markets and the US, from 1980 to 1990, they test for difference in correlations across different variance regimes – for the relationship between the US and the other seventeen markets. Ramchand and Susmel conclude that, during periods of high US variance (market volatility), international stock markets are highly correlated with the US markets. The variance was deemed as time and state varying, which by implication means that the covariance also changes over time.

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[40] This paper was first circulated as UCSD working paper

[41] Issues relating to time varying stock market integration are discussed in substantial detail when we look international asset pricing models and international multifactor models in the next two sub-sections

[42] Dynamic volatility models and application are discussed in subsequent sections.

[43] They implement the Switching Autoregressive Conditional Heteroscedasticity Models (SWARCH) introduced by Cai (1994) and Hamilton and Susmel (1994). ARCH models are discussed in the Asset Pricing Models and Volatility transmission sections. In a related analysis Hamilton and Lin (1996) used a regime-switching model to document evidence of high stock market volatility during periods of severe market downturn – economic recession. Although this study only focuses on the US we should not be surprised that studies looking at a number of international stock markets are finding high correlations between stock market indices during periods of highly volatile bear markets.

This finding is consistent with Longin and Solnik (1995)[44]. Very recently and from a slightly different perspective, Bansal and Lundblad (2002) have provided evidence supporting the findings in Longin and Solnik (1995). They used a Campbell and Shiller (1988a)-type present value model with given cash flow dynamics, which is deemed to have large effects on implied equity prices, volatility, and asset betas[45].

Perhaps, the seemingly overwhelming evidence of highly correlated international stock markets during highly volatile bear markets should be not be entirely surprising because, due to Schwert (1989b) and Hamilton and Lin (1996) we know that that the aggregate level of stock market volatility is time-varying and is much higher during economic recessions. Errunza and Hogan (1998) examined the relationship between volatility and real economy for set of European countries. Their evidence suggests that past variability in macroeconomic variables significantly affect the variability in stock returns. Nonetheless, the fact that correlations between international stock markets are higher during periods of high volatility has profound implications for international portfolio choice. In particular, in a highly volatile market, internationally diversified portfolios should have provided investors with necessary immunisation because these sorts of portfolios are, in general, supposed to yield diversification gains through risk reduction. Therefore, the fact that correlations are higher during high volatility periods renders the use of international diversification – as a means of risk reduction – virtually obsolete. Very recently, new empirical evidence on further analysis of the relationship between the correlation structure of international stock markets and

[44] Longin and Solnik used a simple Generalised ARCH model [a GARCH(1,1) model]. More on this later

market volatility has become available. Jacquier and Marcus (2001), Longin and Solnik (2001), Das and Uppal (2001), and Ang and Bekaert (2002) have offered some new insights.

Jacquier and Marcus (2001) used a traditional single index model to examine the time variation of the correlation structure of both domestic and international asset returns[46]. They expressed the squared correlation between the return on a countries index and the MSCI world market index as function of the volatility of the MSCI world market index. Their times-series regressions indicate that short-horizon cross-country correlations can be attributed to the variation in the volatility of the MSCI world index. An increase in the volatility of the MSCI index would therefore increase the systematic risk in the single index model of country returns, which then increases the correlation of returns across all countries. Jacquier and Marcus' results have implications for forecasting the covariance between countries. This information is invaluable to international asset allocation managers attempting to minimize the risk of their portfolio positions.

Longin and Solnik (2001) on the other hand, claim that, the relationship between high correlation and high market volatility is a "spurious" one and suggested the use of "extreme value theory" to specify the distribution of conditional correlations. They considered the possibility that returns – large absolute returns[47] – are characterised by a class of extreme value distributions instead of the widely 'accepted' multivariate normal distributions. "Extreme value theory" models the tails of the marginal distribution and the dependence structure of extreme

[45] They use an ARIMA (1,01) (no unit root) to describe the cash flow growth process for which they provide empirical support.
[46] See Sharpe, et al. (1999) for an excellent discussion of index models.

observations (beyond a given threshold) – it specifies the distribution of correlation conditional on large negative or positive returns under the null hypothesis of multivariate normality with constant correlation. Longin and Solnik rejected multivariate normality for negative tail but not the positive tail. In other words, the correlation of large positive returns is not inconsistent with multivariate normality but the correlation of large negative returns is much greater than accepted. This correlation of large negative returns is known as "asymmetric exceedance correlations". The empirical results from Longin and Solnik (2001) is particularly important because it suggests that correlation between international stock returns increases in bear markets but, not in bull markets. This means that volatility does not affect the correlation structure of international stock returns during buoyant market periods. Susmel (2001) have also provides evidence for extreme value distribution for stock markets. He looked at data for both emerging markets and industrialised stock market and concluded that emerging market returns appear to have fatter tails than industrialised markets and suggests that this increases the benefits of international diversification for a US investor who diversifies into Latin America and who uses the 'safety first' principle[48].

The findings of Longin and Solnik (2001) appears to be at odds with some of the other studies we have already discussed; especially, the MVGARCH model with constant conditional correlation. However, this should not sound alarming because Longin and Solnik did not reject multivariate normality for the positive tail of the correlation distribution. An explanation offered by the Longin and Solnik is that, tests of multivariate normality must be properly specified when conditioning on

[47] Large absolute returns are returns during highly volatile periods.

[48] Under the safety first criterion, an investor minimizes the chance of a very large negative return by setting a threshold below which the portfolio return should not go.

some realised level of returns or volatility because, under these assumptions, correlations conditioned on the level of volatility is expected to substantially increase with levels of volatility. Longin and Solnik (2001) modelled the asymptotic properties of the tail of the distribution instead, using "extreme value theory" (EVT). This methodology develops a formal statistical method to test "whether correlations of large returns is higher than expected under the assumption of multivariate normality". We note this is a new line of research and is very recent and should be viewed in that context. Although it is a major new development in the literature, further empirical applications, for example using different countries and data, are required to verify Longin and Solnik's results especially in light of Engle (2002a) new class of MVGARCH models – the dynamic conditional correlation (DCC) specification.

Das and Uppal (2001) considered portfolio selection when perfectly correlated jumps across countries affect international equity returns. A multivariate system of jump-diffusion process in which the arrival of jumps is simultaneous across markets is used to model international equity returns. Their results indicate that these jumps constitute a systematic risk and marginally reduce the gains from international portfolio diversification.

Ang and Bekaert (2002) are the most recent contributors – to this important debate about the relationships between correlations between market indices and volatility – that we are aware of. They used a regime-switching model to solve a dynamic portfolio choice problem in which a US investor is faced with a time-varying investment opportunity set characterised by correlations and volatilities that increase in bad times. Their regime-switching model provides evidence that supports the "asymmetric exceedance correlation" notion reported in Longin and Solnik (2001). Like Longin and Solnik (2001), Ang and Bekaert (2002) showed that standard models such as multivariate normal and asymmetric GARCH models do not capture "asymmetric exceedance correlation". Although the use of a regime-switching type model in analysis of correlation structure or volatility is not entirely new[49], Ang and Bekaert's analysis solves a dynamic asset allocation problem in the presence of regime switches for investors with constant relative risk aversion preferences. The investors' choice problems is then analysed under different types of regime-switching scenarios. Overall, Ang and Bekaert (2002) provided evidence of a "high-volatility, high-correlation regime which tends to coincide with a bear market" although, "the evidence on higher volatility is much stronger than the evidence on higher correlations"[50]. Although these recent studies[51] provide new evidence, they have not altered the fact the investors' portfolio allocation or diversification decision is a function of the distribution – be it unconditional, conditional, a jump-diffusion process, or an "extreme value" distribution – of returns or return correlations.

It is also important to note the question of increased stock market volatility is in itself debatable. Schwert (1989b) has shown that there is no discernible long-run trend in the volatility of the U.S. equity market as a whole. However Campbell, et al. (2001) suggests that between 1962 and 1997 there was an upward trend in idiosyncratic volatility in the US stock market. Idiosyncratic or firm level volatility is the volatility of the idiosyncratic component in a standard market model for

[49] See for example the studies by Hamilton and Lin (1996) and by Ramchand and Susmel (1998b), which have already discussed.

[50] This evidence on higher volatility in bear markets is consistent with earlier studies by Schwert (1989b) and Hamilton and Lin (1996).

[51] Das and Uppal (2001), Longin and Solnik (2001) and Ang and Bekaert (2002)

example. This finding has implications for the correlation structure of international equity markets. A similar finding relating specifically to industry level volatility was reached in independent work by Schwert (2002) his study of the technology and telecoms sector in the US stock markets. He suggests that most of the recent increases in market volatility were due to technology bubble busting. The technology and telecoms sector have been the most volatile sector in recent years. The evidence from these studies is that on average stock market volatility tends to return to its long-run mean value.

Rising firm level or idiosyncratic volatility is important for a number of reasons. First, the number of securities needed to obtain a reasonably well diversified portfolio increases as idiosyncratic volatility rises relative to market volatility, which increases the risk for investors that hold under-diversified portfolios[52]. Second, Goyal and Santa-Clara (2001) find that, contrary to modern portfolio theory, diversifiable firm specific volatility commands a risk premium in the U.S. They hypothesise that this is because investors hold non-traded assets such as human capital or private business investments that add background risk to their traded asset portfolio decisions. If the risk of non-traded assets is related to the total risk of traded equity (and not just market risk) then idiosyncratic volatility will be associated with equity returns. Third, in explaining the poor explanatory power of common asset pricing models, Roll (1988b) argues that high idiosyncratic volatility as a proportion of total volatility suggests that investors might be trading on frenzied information not relating to the market or investor might be trading on firm-specific information which is uncorrelated with the market. The implications

[52] Several recent papers have pointed to a surprisingly low degree of investor diversification including Falkenstein (1996), Heaton and Lucas (1996), Heaton and Lucas (1997, 2000), Barber and Odean (2000), Bernartzy and Thaler (2001) and Vissing-Jorgensen and Moskovitz (2001).

of low investor diversification in the context of international portfolio diversification are addressed below when we assess the "Home Bias" puzzle. In the final empirical chapter of this thesis we study volatility spillovers at an industry and market level. We utilise some recent innovations in correlation and volatility modelling.

We have now shown that there is strong evidence, overall, which suggest that international correlation between stock market indices have not increased considerably and that stock index correlations changes over time. This evidence should be encouraging to the international investors who would like to maximise the gains from international portfolio diversification. And, given that anecdotal evidence also suggests that the investment barriers between nations are gradually declining, it is surprising that both academic researchers and market participants have come to observe what is known as the 'Home Bias' or international diversification puzzle.

The home bias refers to the fact that despite the noticeable gains from international portfolio diversification, most domestic investors prefer to invest their wealth in their domestic stock markets rather than investing abroad – investors portfolios appears to be hugely dominated by domestic investments going beyond what standard portfolio theory would suggest. Over the last decade or so, financial economists and practitioners alike, attempting to resolve this puzzle, have conducted extensive research on this subject. We will now review some of the key issues.

Issues relating to imperfect or incomplete diversification have long been discussed in the literature[53]. Recently, French and Poterba (1991), Uppal (1993), Cooper and Kaplanis (1994) and Tesar and Werner (1995) have conducted rigorous research on the home bias question (the international diversification puzzle)[54]. French and Poterba (1991) used a utility maximisation framework[55] to analyse investor preferences and behaviour in order to determine whether the consequences of incomplete or imperfect diversification are indeed costly. They conducted analysis for the six largest stock markets in the world[56] and reported significant differences in the expectations for different investors' assessing the same market. Specifically, they find that domestic investors expected substantially higher annual returns on investments in domestic shares. In a further analysis, an assessment of domestic investors expectations when faced with either an internationally diversified value-weighted portfolio or a set of domestic stocks, revealed that, "investors expect domestic returns that are systematically higher than those implied by a diversified portfolio".

French and Poterba offered both institutional and behavioural explanations for their results. Institutional and behavioural factors were regarded as having a limiting effect on investors' ability to hold internationally diversified portfolios. Examples of institutional factors are those that are widely described in the literature as

[53]For example, Lease, et al. (1974) in a survey research article about individual investor attitude and attributes reported widespread incomplete diversification among many US investors with most of them holding relatively few stocks in their portfolios.
[54] Studies such as Black (1974), Solnik (1974a), Stulz (1981b), Sercu (1980) and Adler and Dumas (1983) showed that domestic investors may bias their portfolios towards domestic assets because of taxes on foreign assets or because investors generally consume more domestic goods, they are rather inclined to hedge against domestic inflation by holding more domestic securities in their portfolios.
[55] They used a utility of wealth model, which is defined under constant relative-risk-aversion. The utility function is maximised subject to the expected mean returns being equal to a risk-aversion parameter multiplied by optimal portfolio weights and the variance-covariance matrix. See French and Poterba (1990) and French and Poterba (1991), for details on calibration.
[56] They are the US, Japan, UK, France, Germany and Canada stock markets.

barriers to international investments[57]. But, according to French and Poterba, these factors are "unlikely to explain the low level of cross-border equity investments". Tax burden on foreign equity holdings, for example, were, in general, identical to domestic tax liability on equity holdings[58]. Transaction costs were also considered as possible explanations but the rational for these is somewhat confusing, at the very least. There has been a vast increase in the levels of cross-border investments, which indicate that transaction costs could not possibly explain the puzzle. In fact, the other major empirical research conducted on this issue – by Tesar and Werner (1995) – strongly discounted the likely role of variable transaction costs in explaining the home bias puzzle.

Tesar and Werner (1995) document high volumes of cross-border capital flows in five major OECD countries and report a high turnover rate on foreign equity investment compared to domestic investments. Their extensive survey research confirms the findings in French and Poterba (1991) – There is a strong bias towards domestic securities in investors portfolio despite gains in risk reduction obtainable from holding an internationally diversified portfolio. The effects of currency on domestic investor preferences have also been considered. Brealey, et al. (1999) found that currency risk on its own does not explain the home bias puzzle. Financial innovation and the increased use of derivative products for hedging, mitigates the effects of exchange rate volatility on a domestic investors' internationally diversified portfolio.

[57] These are discussed in detail in the last few paragraphs of this section

[58] It is important to note however that taxation rules do change and it likely that the scenario or tax regime observed by French and Poterba may have changed. Nonetheless, the substantive point is that there little difference, in magnitude, between domestic and foreign tax liability on equity holdings. This cannot explain the significant home bias in investors' portfolio construction.

Rowland (1999), on the other hand, offered a different view to those offered by Tesar and Werner (1995). Rowland describes the home bias puzzle (or rather justifies domestic portfolio bias) and, explains the high turnover rates of international assets held by domestic investors by, employing an intertemporal portfolio choice model that incorporates proportional transaction costs. He offered the following explanation: "The international turnover rate is greater than domestic rate because the average holdings of the international asset are small, not because the volume of trading is large". Rowland's model[59] is structured in a way that it can simultaneously explain both the domestic bias of portfolio holdings and the observed structure of turnover rates. Time series simulation results of this model reveal that, proportional transaction costs increases the transition time for investors holding a purely domestic portfolio but want to move to an internationally diversified portfolio. If proportional transaction cost increases, investors would normally shift to a passive investment strategy of portfolio reallocation and the transition time from holding a domestic portfolio to holding internationally diversified portfolio increases hence the observed home bias puzzle[60]. Effectively, Rowland (1999) is suggesting that the home bias puzzle is a mere characterisation of the nature of international investments and is therefore consistent with international investment theory.

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[59] This model is elaborate. We therefore do not attempt to reproduce it here. It based on maximising the expected lifetime utility of consumption where the individual's objective function comprises both the utility function and a value function, which holds between two time periods. Rowland uses a continuous-time characterisation (a geometric Brownian motion process with a drift) for the real asset price. The individual's preference (utility) is a function of the real return on an asset, which is in turn a function of the real price of the asset. See Rowland (1999) pages 149 –153 for an exposition.

[60] According to Rowland (1999) passive portfolio allocation strategy is costless but diversification benefits are obtained over much longer time horizon. The investor would generally balance the use or an active or a passive strategy by actively reallocating portfolios up to the point where the marginal benefit of diversification is equal to the marginal cost of reallocation (international) Rowland (1999).

Uppal (1993) used a two-country general equilibrium model to investigate whether investors' preference for domestic goods would normally lead to a preference for domestic securities. The investors' preference for either a domestically diversified portfolio or an internationally diversified portfolio is considered to be dependent on his/her level of risk aversion. Uppal showed that investors that are less risk averse would have an optimal portfolio biased towards domestic assets compared to those who are more risk averse, who exhibit a preference for foreign asset. This is primarily due to the specification of Uppal's model and its implication. As Uppal puts it: "*the exchange rate, derived endogenously, is negatively correlated with the return on foreign assets, and therefore, the translated return on foreign stock is less risky than that on the domestic stock*". In other words, Uppal is suggesting that, the high proportion of domestic goods in an investor's total consumption basket could not explain the home biased puzzle. If anything, investor's should be investing in foreign assets in order to reduce risk[61].

Cooper and Kaplanis (1994) used a model of international portfolio choice and equity market equilibrium to examine the question of home bias in investors' equity portfolios. The main approach in this study is to determine whether the observed home bias in portfolios is due to domestic investors trying to hedge against stochastic inflation risk. The model is an extension of the Adler and Dumas (1983) continuous-time portfolio choice model[62]. Cooper and Kaplanis augmented this model by integrating inflation risk and deadweight costs. The deadweight cost

[61] The characterisation of Uppal's two-country general equilibrium model constrains investors from consuming foreign capital stock and introduces a proportional cost for transferring goods from one country to the other. The presence of proportional costs for transferring capital induces endogenous deviations from the law of one price (Purchasing Power Parity – PPP). These deviations should represent gains from international portfolio diversification because of the negative correlation between endogenous exchange rates and the return on foreign assets and, this correlation increases with risk aversion. The frequency with which capital is transferred between countries also increases with risk aversion. The more risk-averse investor therefore prefers the foreign assets. See Uppal (1993) for a technical exposition

is used to explain the part of the home bias that is unexplained by inflation risk[63]. The empirical evidence suggests that, depending on the investors' level of risk aversion, hedging against inflation risk could explain the home bias puzzle. If investors have very low levels of risk aversion and, equity returns are negatively correlated with domestic inflation. The investors' low level of risk aversion generates levels of deadweight costs that trigger the home bias[64]. In terms of the relationship between an investor's level of risk aversion and the home bias in portfolio investment, Cooper and Kaplanis (1994) findings are consistent with the study by Uppal (1993).

The literature on the home bias puzzle is expanding rapidly[65]. International national macroeconomists, for example, have used various international trade theories to conceptualise or explain the home bias puzzle[66]. Other suggested explanations for the home bias in domestic investors portfolios include, the hedging of relative price risk, Cooper and Kaplanis (1994); informational asymmetries between domestic

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[62] See section III equation 1 in Adler and Dumas (1983). The basic idea of the model is the selection of optimal portfolios that maximise the gains from international portfolio diversification.
[63] Deadweight cost in this context would refer to the excess burden of investing abroad. This is the test of the efficiency of international diversification despite the gains in risk reduction obtainable from investing abroad. The idea of deadweight cost/loss or debt comes from studies of taxation and the efficiency of taxation.
[64] In a related investigation, Stulz and Wasserfallen (1995) addressed the question of deadweight cost in international investment. Specifically, they show that due to the deadweight cost of holding domestic and foreign investment, domestic and foreign investors would exhibit differing demand for domestic investment. In countries such as Switzerland, for example, there are shares that cannot be bought by foreign investors and others that can only be bought by foreign investors. Because of this home bias in asset holdings, shares held by foreign investors sell at a premium. See Stulz and Wasserfallen (1995) for details. Coen (2001) also used an international capital asset pricing model (CAPM) with human capital and deadweight cost but found that hedging human capital does not resolve or explain the home bias puzzle. Coen results were unlike those discovered by Bottazzi, et al. (1996) who found that the returns on human capital could partly explains the home bias puzzle.
[65] Lewis (1999) provides a review of this growing literature
[66] Baxter, et al. (1998) for example looked at the role of nontraded consumption goods or nontraded factors (human capital) of production in explaining the home bias puzzle. Portes, et al. (2001) used a gravity model for trade – this model explains trade flows between nations using GDP and distance – to show that informational asymmetries are responsible for the strong negative relationship asset trade (financial assets and goods trade) and distance. Jermann (2002) used a general equilibrium model driven by productivity shocks to study the effect of labour supply for optimal international diversification and explaining the home bias puzzle. We will not attempt to review these studies here.

and foreign investors, Cooper and Kaplanis (1994), Ueda (1999) and Hasan and Simaan (2000); domestic investors' preference for only large foreign firms, Kang and Stulz (1997); and corporate governance – "when firms are controlled by large investors, portfolio investors are limited in the fraction of the firm they can hold" – Pinkowitz, et al. (2001). This suggests that, even with the removal of international investment barriers, the home bias might not disappear completely.

Although most of the major studies investigating the home bias puzzle utilised a general equilibrium-type model of international portfolio choice, these studies have also alluded to the possibility that widely observed barriers to international investments and, sometimes, the over-optimism of domestic investors towards home assets are somehow responsible for this bias. Apart from informational asymmetries, it is however, very difficult to provide both a theoretical and an empirical explanation for the home bias using the observed barriers to international investments. An interesting and perhaps crucial finding is the recent suggestion by Errunza, et al. (1999) that gains from international diversification are not statistically and economically different from those attainable through home-made diversification in domestic portfolios that mimic foreign indices[67]. Their evidence is based on standard mean-variance spanning[68], unconditional correlations, conditional correlations (GARCH framework – constant conditional correlations and generalised conditional correlations) and, tests of the Sharpe ratio – a performance measure. This evidence seems to suggests that with the increased globalisation of capital markets and increasing number of multinational

[67] The mimicking international portfolio constitutes mainly multinational corporations, close-end country funds – an investment company that invests in a portfolio of assets in a foreign country and issues a fixed number of shares domestically – ,and ADR's

[68] See Huberman, et al. (1987) or Bekaert and Urias (1996) for details

corporations operating domestic investors need not go abroad to achieve the benefit of global financial architecture.

To conclude our discussion of the major issues in international portfolio diversification, we will briefly summarise the general barriers to international investments[69]. Eun and Janakiramanan (1986), Bekaert (1995) , Demirguc-Kunt and Huizinga (1995), Erb, et al. (1996c) and Solnik (1999) provide a good syntheses of these barriers. Solnik (1999) lists the following as the key impediments to international barriers: psychological barriers, legal restrictions, transaction costs, discriminatory taxation, political risks, and exchange risks.

Psychological barriers deals mainly with the fact that some international investors might be unfamiliar with a particular market or lack the necessary detail information to convince them that it is possible to maximise the risk return trade off by investing in 'unfamiliar territory' especially, emerging equity markets. Language barriers and potential culture shock have also been regarded as a psychological bar to international investments. The over-optimism of domestic investors to home assets might also be regarded as psychological barrier to international portfolio diversification.

Legal restrictions have long been regarded as the single most important barrier to international investments. In the 1970's and early 1980's most governments – both developed and emerging markets, through their regulatory bodies, had some form of legal restriction to international investments whether by its citizens wishing to

[69]The existence of barriers or restrictions to international investments has been the main theoretical tool in most theoretical models of capital market integration, segmentation or partial integration. We survey these models in the next sub-section of this chapter.

invest abroad or foreign investors who want to invest in the local market. In the UK for example legal restriction on international capital investments emanating from the UK were only removed after the election of the Thatcher government in 1979. This ended nearly fifty years of restricted capital movements between the UK and other international markets[70]. Bekaert (1995) discussed the various exchange and capital controls that affect investments in emerging markets. The repatriation of dividends and capital from emerging markets are sometimes restricted. There are also direct restrictions such as a required minimum investment period. Other forms of foreign ownership restriction or investments barriers include a percentage capping of the number of shares held by foreign investors in general or in specific domestic firms. Sometimes, some domestic firms have shares that are exclusive to foreign investors (or to be traded between foreign investors only) but are offered at a premium. Stulz and Wasserfallen (1995) and, Domowitz, et al. (1997) for example, have provided both a theoretical characterisation of these types of barriers and reasonable empirical evidence for Switzerland and Mexico respectively. The empirical evidence suggests that legal restrictions of this nature induce both segmentation of capital markets and a 'home bias' in investors portfolios. Bailey, et al. (1999) have provided evidence of the relationship between the flow or foreign investment into a country's stock market and level or fraction of shares that are restricted to domestic investors only in 11 stock markets. Their evidence suggests that there is a strong correlation between the flow (demand) of investment and the size of the premium (percentage spread) between the restricted and unrestricted shares in these markets. They also suggested that investor sentiment drives this premium. In particular, foreign investors are attracted to countries with good credit ratings and large liquid stocks. It appears that international investors might not be

[70] See Taylor and Tonks (1989) for a discussion.

troubled by market segmentation and would be prepared to pay for the benefits of international diversification whenever the price is right.

Discriminatory taxation and other financial accounting restriction are also forms of legal restrictions. The existence of differential taxation rules for dividends or capital gains earned by foreign and domestic investors in the same market are regarded as serious impediment to international investments. Demirguc-Kunt and Huizinga (1995) provides empirical evidence for the existence of discriminatory tax regimes in developing countries and discusses the implications of such practices. They noted that, despite the fact that developing countries have not substantially reduced the investment tax burden on foreign investors, other innovative methods such as debt equity swaps and the establishment of country equity funds, are being employed to increase foreign investor participation in these markets. Solnik (1999) also contemplated the possibility that withholding taxes might lead to double taxation for some investors[71].

The level of transactions costs that accompanies investments in foreign markets are generally regarded as very high. Solnik (1999) noted that international transaction costs, management fees and custodian services are very high and, obtaining access to sources of information in international financial markets is often very costly. International investors require adequate information on financial markets and detail

[71]A withholding tax is tax levied at a standard rate on all receipts of income from wages or dividends, irrespective of the individual's tax liability. It is important to note however, that taxation and other financial accounting rules are rapidly changing across nations. Anecdotal evidence suggests that these types of barriers are gradually being reduced. In addition, international accounting bodies are taken a progressive approach to the standardisation of accounting practices across nations. French and Poterba (1991) also noted that, the difference between the tax burdens on domestic and foreign investors might not be that great, particularly to justify the observed home bias in investors portfolios. The near-harmonisation of financial accounting regulatory structures across nations – although as yet a distant prospect – is a good prospect and are generally muted in

company assessment before they invest[72]. Obtaining the correct information is very expensive. Exchange risks are also considered to be a very important barrier to international investment because foreign investors are effectively exposed to the local market risk and the potential fluctuations of the local currency relative to the foreign investors' domestic currency. It is however, generally accepted that this risk can be minimised if the investors holds an internationally diversified portfolio that is hedged for foreign exchange risks.

Political risks or the lack of stable political institutions in foreign countries play a very important role in the portfolio diversification or investment decisions of the international investor. Such risks are perhaps not much of an issue in markets of highly democratised and developed countries but are serious concern in some emerging or markets in least developed countries. Diamonte, et al. (1996) examined the importance of political risks in emerging and developed stock markets. Using the political risk component of the country risk index published by *International Country Risk Guide* (ICRG) they provide a comparative analysis of the effects of changes in political risks on markets returns in 45 international stock markets. They reveal a differential impact on returns and emerging stock markets were more susceptible to changes in political risks than developed stock. Analysts who could forecast changes in political risks could very well forecast changes in stock returns. Erb, et al. (1996b) have conducted a more comprehensive analysis of the effects political, economic and financial risks have on stock returns. They investigated the evidence for 117 countries by pooling together data from two

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international accounting circles. Also, the teaching of international accounting rules in third year undergraduate accounting courses or in professional accounting examination is now standard.

[72] Adequate information would require information beyond the standard country credit rating or firm credit rating that is published by international credit rating agencies (For example, Moodys Associates or S&P)

major sources – The ICRG and the *Institutional Investor (II)* country credit ratings[73]. The focus of their project was to investigate whether such widely used international risk indices contained information about expected returns. Generally, these indices contained information about future expected equity returns but unlike Diamonte, et al. (1996) the evidence on the information content of the political risk index was very weak and lacks the ability to produce abnormal returns[74]. Although Erb, et al. (1996b) used a very well structured portfolio rebalancing methodology to factor in the effects of political risks and a good time series and cross sectional analysis of the relationship between political risk and market return, their results of low explanatory power for political risk is perhaps not entirely surprising. Bekaert (1995) and Solnik (1999) have noted that barriers to international investments are very difficult to quantify or measure.

Overall, both anecdotal and empirical evidence seems to suggests that barriers to international investments are gradually disappearing and the flow of international portfolio investments between nations have grown considerably especially in the last decade, [Demirguc-Kunt and Huizinga (1995), Bekaert (1995) and Solnik (1999)]. Even when there are severe barriers to international investments in a domestic market, large firms have sought to maximize the benefits of international diversification by cross-listing on major stock exchanges.

By cross listing abroad, companies can raise more funds at a lower cost of capital and also have the ability to diversify their exposure to global market risks. In the US for example, foreign firms can cross list their stocks by operating on the over-

[73] Other international institutions such as the Economist Intelligence Unit (EIU) also offer extensive databases on country risk assessments.
[74] Financial, economic and composite-risk rating were found to have significant predictive ability.

the-counter market (OTC) or by issuing what is known as American Depository Receipts (ADR). The equivalent cross-listing vehicle in the UK is the Stock Exchange Automated Quotation International (SEAQ-I)[75]. Although expensive in some respects–for example, companies listing in the US or UK should meet minimum regulatory requirements and financial statements must adhere to generally accepted international accounting standards–ADR's and SEAQ-I's are both a vehicle for raising capital internationally and an instrument for international diversification for the US or UK investor who would otherwise not invest abroad due to the barriers of international investments discussed above. This literature on the dual listing of stocks is expanding rapidly[76]. Researchers have looked at mainly the behaviour of the market price (expected returns) of the stock around the listing period and, how cross-listing affects the liquidity of the stocks. The primary purpose for this is to prove or disprove the *segmentation hypothesis.*

The *segmentation hypothesis* was due to amongst others, Alexander, et al. (1987, (1988))[77]. Generally speaking, the *segmentation hypothesis* "suggests that international listing will lead to a reduction in the expected return on the security if capital markets are either completely or "mildly" segmented", (Alexander, et al. (1988))[78]. Because, cross-listing of securities gives firms of segmented capital markets the opportunity to diversify global markets risks, this will eventually lead to a reduction in the expected returns. Empirical support for this hypothesis have been provided by, for example, Torabzadeh, et al. (1992), Serra (1999) , Foerster

[75] Serra (1999) discuses the various institutional issues surrounding the cross listing of stocks discuses the different types of cross listing methods available including depository receipts (DR's) and Global Depository Receipts (GDR's)
[76] An extensive review of this growing literature – especially, the valuation and liquidity effects of the listing decision – can be found in the monograph by Karolyi (1998).
[77] Domowitz, et al. (1998) and Foerster and Karolyi (1999) for example, have also tested the segmentation hypothesis. See Karolyi (1998) for more details.

and Karolyi (1999) and Foerster and Karolyi (2000)[79]. The driving force behind the decision to cross-list abroad is the characteristics of the international market relative to the domestic market especially, in terms of liquidity and size. Pagano, et al. (2001) suggests that European markets are more likely to cross-list in more liquid and larger markets, and in markets where several companies from their industry are already cross-listed. There is also the question of whether the dual listing of stocks increases liquidity of the shares and liquidity in the domestic market. On this issue, Karolyi (1998) concluded that "share liquidity improves overall, but depends on the increase in total trading volume, the listing location and the scope of foreign ownership restriction in the home market". As stated earlier, the literature on the cross-listing of stock is growing and a number of other studies in the capital market integration literature have touched on this issue in some respect. This is not entirely surprising because one of the methods used to test whether markets are integrated is to look for the existence of stock price arbitrage for identical securities listed in different market. Whenever appropriate, in the reminder of our survey, we will refer to this issue again. Investors have also sought to maximise the benefits of international diversification (i.e. reducing overall systematic risk), without incurring the costs of the severity of capital controls, by investing in internationally diversified mutual funds. However, tests of the performance of these funds suggests that investors are better off if they hold an international equity index such as the Morgan Stanley Capital International (MSCI) world index (Cumby and Glen (1990)). Later we will point out that a multifactor world for stock returns is perhaps the most appropriate.

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[78] Alexander, et al. (1988) hypothesised that; international listing of the common stock of a foreign firm in the United States will lead to a reduction in its expected returns.

[79] There are however some exceptions to this. For example, some researcher have found that the risk in the cross-listed market have increased although the risk in the domestic market did decrease, see for example Jayaraman, et al. (1993). Chan, et al. (1996) found that overall risk increased for cross-listed stocks.

To summarise, this sub-section illustrates the logic that lies behind international portfolio diversification. It shows that there are substantial benefits for investors holding internationally diversified portfolios primarily in the reduction of overall portfolio risk (systematic risk) and also in the reduction of the cost of capital of specific investment projects. We have also addressed all the known methodological issues that have been identified in the extant literature on international portfolio diversification particularly those relating to the use of the correlation structure of international stock returns as the guiding principle of international diversification. Conditional correlation methods are deemed to be more appropriate in these circumstances. New thinking in this area includes, dynamic conditional correlation models, perfectly correlated jumps – described by a jump diffusion process – across international stock markets, "extreme value" theory, and regime changes. Issues relating to home bias puzzle have also been discussed. We have established that home bias puzzle is still a puzzle but potential explanation would include for example, barriers to international investments, the breakdown of purchasing power parity, asymmetric information, the hedging of human capital or other non-traded goods, the over-optimism of domestic investors towards their domestic capital markets, and the effects of corporate governance especially, when companies are controlled by large investors who by implication restrict the fraction of the firm a portfolio investor could hold. We have looked at the stylised facts on the major barriers of international investments and also illustrated the fact that international firms and investors alike have attempted to reduce the severity of these barriers by maximising the advantage of cross-listed securities in larger liquid markets. Firms have cross-listed abroad in order to reduce global market risks. With cross-listed securities, Investors have invested in securities that they would have otherwise not invested in due the existence of foreign ownership restrictions in the cross-listed firms' domestic capital market. However, we have also shown that, generally, there is evidence that these barriers to international investments are being dismantled due to the increased globalisation of international capital flows. In the next sub-section we look at the various international asset pricing theories that have been employed in tests of capital market integration.

2.32 International Asset Pricing Models

Tests of international asset pricing models and capital market integration evolved out of tests of the standard domestic Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965), Mossin (1966), and the intertemporal CAPM (ICAPM) of Merton (1973). Domestic tests of the CAPM are done under conditions of completely segmented markets where the optimal risky portfolio is the domestic market portfolio. In the international version of the CAPM, the return generating process of securities or portfolios is assumed to be dependent only on the risk premium on the world market portfolio – the optimal risky portfolio in this case. This restriction is due to the assumption of perfectly integrated capital markets. Researchers testing capital market integration using an international asset pricing framework have either assumed that markets are completely integrated thereby excluding a role for national or domestic factors in the return generating process or, have assumed that markets are partially integrated – the midway between complete segmentation and perfectly integrated stock markets; this allows for the possibility that domestic risk factors might be priced up to a point.

The literature can be understood from perhaps two perspectives. We can either focus on the analysis of international investors' consumption or investment opportunity sets (see for example Stulz (1995a)), where a continuous-time model[80] of portfolio choice is examined under conditions of no difference in the consumption and investment opportunity sets of international investors, conditions where there are differences in consumption opportunity sets and, conditions were there are explicit barriers to international investments. Various asset pricing models are then showed to be special cases of a continuous-time model of the returns of an asset in terms of the price of the consumption good, and the maximisation of the indirect utility of wealth for an investor defined over goods – what Stulz (1995a) calls "the asset demands equation"[81]. Alternatively, one can simply discuss the key models in terms of their assumptions and key findings. We will opt for the later case because it allows us to focus on the key results instead of trying to deduce mathematical relationships between the various international asset pricing models or models of international portfolio choice.

Respectively, we describe the following models: the international CAPM – also known as the international Asset Pricing Model (IAPM), the international Arbitrage Pricing Theory (IAPT), international consumption CAPM (ICCAPM), and other single factor and multifactor models of international capital market integration. In each of these models, where necessary, a distinction will be made between unconditional and conditional versions, and if the role of key factors such as currency risks and barriers to international investments are included, will be highlighted. We will also look at the recently developed model of time varying world market integration (Bekaert and Harvey (1995)) – an excellent contribution

[80] The mathematical analysis in most of these type of models are due to Merton (1973). Merton (1990) provides and exhaustive synthesis of these models.
[81] See Stulz (1995a)

to the literature which combines a number new econometric methodologies in testing the IAPM.

One of the first theoretical extensions of the domestic CAPM to an international setting was by Solnik (1974a). Solnik's equilibrium model - the International CAPM (IAPM) – was based on the ICAPM of Merton (1973). In addition to the assumption of the standard domestic CAPM[82], this model assumes that Investors use their home currency as a base currency and the world market portfolio is partly hedged against currency risk. In other words, there is an additional risk premia which is linked to the asset's sensitivity to currency movements. Merton's ICAPM is an excellent framework for tests of models that contain additional risk premia. A version of the basic Solnik (1974a) model is given in Solnik (1999) as:

$$E(R_i) = R_0 + \beta_{iw} \times RP_w + \gamma_{i1} \times RP_1 + \gamma_{12} RP_2 + \cdots + \gamma_{ik} RP_k \quad (2.1)$$

Where

R_0 is the risk-free interest rate,

β_{iw} is the sensitivity of asset *i* to market movements,

RP_w is he world market risk premium equal to $E(R_w) - R_0$,

γ_{i1} to γ_{ik} are the sensitivities of asset *i* to the currencies 1 to *k,* and,

RP_1 to RP_k are the risk premia on currencies 1 to *k.*

This model contains additional risk premia for exchange rate fluctuations but if there is a world market portfolio that is optimally hedged against currency risk, the model collapses to a traditional CAPM (call it a world CAPM) with a single market risk premium[83]. In actual fact, this model is equivalent to a discrete-time version of

[82] See Copeland and Weston (1988) for a discussion of the basic assumptions of the CAPM and ICAPM.

[83] Solnik is therefore assuming that stock returns in the domestic currency are uncorrelated with exchange rates especially when the world market portfolio is partly hedged for exchange rate

Merton (1973) (ICAPM)[84]. Empirical test of this model was conducted by Solnik (1974b). Solnik found little evidence against the IAPM although; he noted that domestic factors strongly affected stock prices and the domestic CAPM can be consistent with the IAPM when the world market portfolio is the minimum variance portfolio. This therefore means that equity markets are integrated in the Solnik world.

Additional theoretical extensions and tests of the Solnik's IAPM was carried out by Sercu (1980)[85]. Sercu relaxed Solnik's assumptions about the covariance structure of asset returns by allowing the return on the risk-free rate of a foreign country to be perfectly correlated with the growth rates in exchange rates of that country. This affects the composition of the optimal world portfolio that is partly hedged for foreign exchange fluctuations[86]. It now comprises two funds: "a fund of hedged stocks and a pure bond fund"[87]. According to Sercu (1980), the excess returns of hedge stocks are independent of the currency. The main criticism of the Solnik-Sercu IAPM is that it is based on the mean-variance criterion, assumes homogenous expectations with asset returns, exclude the possibility of partial segmentation, assumes constant opportunity sets (a one-period world) and assumes

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fluctuations. According to Solnik (1999), "*the expected return on a foreign risk-free bill is equal to the interest rate in that currency plus the expected exchange rate movement*". The model therefore "*indicates that the expected exchange rate movement should be equal to the interest rate differential plus a summation of risk premia. For example, the expected Swiss franc/US dollar exchange rate movement would be equal to SF/$ interest rate differential plus risk premia linked to the covariance of the SF/$ exchange rate movements with price movements on the market portfolio and on various currencies*". In this IAPM, deviations from relative PPP can occur while investors choose the optimal world market portfolio.

[84] Fama (1998) has shown that if asset pricing conforms to the discrete-time version of the ICAPM and there are a total number of S state variables of hedging concern, one can show that it is possible to find the set of priced state variables are identified. This is what Solnik was trying to achieve. He identified the additional priced variables as the risk premium on the various currencies.

[85] A translated version of Sercu's paper is available on his web site at the following address: http://www.econ.kuleuven.ac.be/tew/academic/intzaken/members/member/publi/thesis.pdf

[86] Stulz (1981), Adler and Dumas (1983) and Solnik (1983) have also questioned the optimality of the world market portfolio. See the discussion on the IAPT.

that price level changes are constant, Sercu (1980). Other unconditional tests[88] of the IAPM include the works by Roll and Solnik (1977) who tested the IAPM for the pricing of forward contracts and found that the model holds "but the premia deviate significantly from those predicted by the model"; Stehle (1977) hypothesised that IAPM can be written in terms of risks that are diversifiable internationally but not domestically and found supportive evidence; and Korajczyk and Viallet (1989) tested various versions of the IAPM and found that IAPM outperforms the domestic CAPM indicating that there are "nontrivial international influences in asset pricing" Cumby and Glen (1990) have also provided evidence – from unconditional tests – that the world market portfolio calculated by MSCI is mean-variance efficient. We discuss conditional models shortly.

An IAPM that incorporates relative Purchasing Power Parity (PPP) is the model by Grauer, et al. (1976) and Hodrick (1981). In these types of models, two strong (somewhat unreasonable) assumptions are added to the domestic CAPM: investors from different countries consume the same basket of goods – the investment opportunity set is constant – and relative PPP holds exactly at any point in time. Grauer et al. assumes that there are multiple goods but the consumption goods are identical in every country hence investors face the same consumption opportunity set. There is however evidence in Solnik (1999) and Stulz (1995a) that consumption preferences differ among counties. There is also ample evidence in the monograph by Marston (1995) and in Solnik (1999) suggesting that PPP does not hold exactly, especially in the short-run and deviations from PPP are a source

[87] This should not be confused with the fact that the model is a two-fund model comprising the country specific fund that contains the investor's domestic risk-free rate (real bond) only, and, an internationally diversified stock-bond fund that is efficient.
[88] Unconditional tests assume that the returns and risk measures are constant over time. The objective in these types of tests is to assess unconditional moment restrictions implied by the

of exchange rate variation. In fact, this is what the IAPM (equation 14) in Adler and Dumas (1983) actually tests. Here the IAPM is derived under conditions that PPP. This has two implications. Firstly, optimal portfolios would differ across countries, and second, the expected return on any asset must include a market premium as well as a currency premium.

Fama and French (1998) [henceforth FF98] proposed a new test of the unconditional International CAPM or IAPM in their analysis on the international evidence on value and growth stocks (portfolios)[89]. The FF98 test is based on the assumption that markets are integrated and investors are unconcerned with deviations from PPP. FF98 tested the international CAPM (IAPM), and a two-factor ICAPM (or APT)[90]. The two-factor ICAPM is based on the multifactor (discrete) version of Merton's (1973) ICAPM. Although FF98 found that the international CAPM (IAPM) was unable to explain the value premium[91], like Solnik (1974b), FF98 found that the IAPM to be a valid model of returns on the markets portfolios of the countries investigated. In other words, all expected returns are explained the sensitivity of the global market return. Although some predictive power has been reported for the world market portfolio (the magic portfolio), the validity (or optimality) of this portfolio has been a long-standing debate. The general conclusion is that it would be very difficult to specify the world market

models. In other words, do cross-sectional differences in average risk explain the differences in average returns? Harvey (1991)

[89] Value stocks are stocks with high ratios of book-to-market equity (B/M), earning to price (E/P), or cash flow to price (C/P). Growth stocks are stocks with low B/M, E/P and C/P. Growth stocks have high earnings and value stocks have low earnings. The value premium exists because value stocks tend to have higher average returns than growth stocks. It is assumed that the value premium is associated with relative distress

[90] The relationship between CAPM and the ICAPM is very straightforward. In the CAPM, only the market portfolio –the minimum variance portfolio – explains the returns on a security. In the ICAPM includes additional state variables whose pricing is not captured by the basic CAPM. This intuition also holds for international versions of these models.

[91] Ibid

portfolio[92]. Griffin (2002) provides evidence which suggests that that the FF98 factors are more country specific rather than global. The evidence for other model specifications examined when we discuss the IAPT and other international multifactor models.

One of the first test of a conditional international CAPM or IAPM for stock markets was conducted by Harvey (1991). Harvey's model focuses on conditional asset pricing restrictions and estimates a conditional CAPM with both constant and time-varying moments. Assuming the capital markets are fully integrated[93], the basic model is:

$$E\left[r_{jt} \mid \Omega_{t-1}\right] = \frac{E\left[r_{mt} \mid \Omega_{t-1}\right]}{Var\left[r_{mt} \mid \Omega_{t-1}\right]} Cov\left[r_{jt}, r_{mt} \mid \Omega_{t-1}\right] \qquad (2.2)$$

Where r_{jt} is the return on a portfolio of country j equity form time t-1 to t in excess of the risk free return, r_{mt} is the excess return on the world market portfolio, and Ω_{t-1} is the information set that investors use to set prices. Harvey calls the ratio of the conditionally expected return on the market index $E\left[r_{mt} \mid \Omega_{t-1}\right]$ to the conditional variance of the market index $Var\left[r_{mt} \mid \Omega_{t-1}\right]$ the '**world price of covariance risk**'. The basic idea of this model is to test the mean-variance efficiency of the world market portfolio in the presence of a conditional information set.

The econometric implementation of this model involves an instrumental variable specification for the information set. The model is then rewritten in terms of these

[92] As Solnik (1983) noted "the world market portfolio will not be optimal in the sense that investors will hold different portfolios, especially "hedged" portfolios......Since the composition of these portfolios depends on the covariance of asset returns with state variables, it is hard to identify such portfolios in order to test the theory."

instrumental variables and is estimated using the generalised methods of moments (GMM) estimator derived by Hansen (1982)[94]. The key findings were that "a single source of risk appears to adequately describe the cross-sectional variation in returns across different countries". In other words, the conditional version of the IAPM holds for a single price for risk (factor) – the conditional covariances. The conditional covariance between the excess returns on the MSCI world index and the respective excess returns on MSCI national indices for various countries were found to be significant. Because Harvey's model was a joint test of market integration and the validity of the asset pricing model, his results indicate that markets were fully integrated and single factor conditional international CAPM (IAPM) is valid. However, the model did not hold for some countries – Japan in particular – suggesting that either the markets were not fully integrated or the asset pricing model is not valid.

Similarly, Dumas and Solnik (1995) conducted conditional tests of the classic IAPM of Solnik (1974a) and Sercu (1980) using an instrumental variable approach; they provide strong evidence in support of a conditional IAPM with time-varying moments; and that exchange rate risks are priced in the conditional IAPM for the four largest equity markets in the world, especially in explaining the expected returns of short-term bonds. Ilmanen (1995) analysed expected returns in the bond market using an instrumental variables approach. Ilmanen provides evidence which supports a one-factor IAPM with constant conditional risk for the bond market. The analysis included both observed and unobservable variables. We revisit these issues

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[93] This automatically leads to joint test of market integration and, that the conditional IAPM holds. Harvey also estimated this model – in the case of Japan – under conditions that the markets were not fully integrated.

[94] See Ferson (1995), Ferson and Jagannathan (1996), and Harvey and Kirby (1996) for a lucid description of conditional beta pricing models and for an overview of Hansen's GMM methods. We offer a brief overview of GMM in the next chapter.

in chapter 5 where we look at the comovements in equity and bond markets for G10 countries.

Other authors have also provided empirical evidence in support of the conditional IAPM using GARCH specifications for the variance and covariances. Engel and Rodriguez (1989) and Giovannini and Jorion (1989) estimated the international CAPM with time-varying second moments specified as GARCH processes for foreign exchange and equity markets. Chan, et al. (1992) used daily data to test the conditional international CAPM (IAPM) allowing for time-varying variances and covariances using a bivariate GARCH-in-Mean process and could not reject the model at conventional levels although, they did find that a two-beta model where each portfolio is a source of risk performs better than the single beta model. De Santis and Gerard (1997) tested a version of the conditional IAPM, which also incorporates GARCH-in-Mean effects and can be estimated simultaneously, for the world's eight largest equity markets[95]. Their evidence suggests that although the restrictions imposed by conditional IAPM is valid; the fact that some of the variation in risk-adjusted excess returns remains predictable during periods of high interest rates means that there are still gains to be obtained from international portfolio diversification[96]. In a related work, De Santis and Gerard (1998) have estimated conditional version of the IAPM in Adler and Dumas (1983) and found that both currency risks and market risks are priced when they are allowed to change over time.

[95] The GARCH-in-Mean model is based on the multivariate GARCH process derived by Ding and Engle (2001), which was originally circulated in 1994 as a University of San Diego Working Paper. Hardouvelis, et al. (1999) have also used a multivariate GARCH-in-Mean model to conduct similar tests of capital market integration.

[96] This predictability occurs when the price of market risk is fixed as positive.

An innovative extension to the conditional asset pricing model suggested in equation 2.2 above is the time-varying world market integration model by Bekaert and Harvey (1995) [henceforth BH]. The model incorporates threshold effects in the form of a conditional "regime switching model[97]" which allows markets to be segmented depending on the regime. It allows the degree of market integration to change over time. National equity markets could be segmented from world capital markets in one part of the sample but subsequently becomes integrated in another part of the sample. Just as the model in equation 2.2, the model also uses instrumental variables – global information variables. Various specifications of the price of risk are suggested including estimating the conditional variances from a bivariate GARCH model (a two-variable MVGARCH model). Their results suggest that a number of emerging markets exhibit time-varying integration and some markets appear to be more integrated contrary to prior knowledge of investment restrictions. Empirical applications of BH including suggestions for possible extensions or alternatives can be found in, for example, Cumby and Khanthavit (1998), Malliaropulos and Priestley (1999), Hardouvelis, et al. (1999) and Carrieri, et al. (2001). However, the idea of characterising financial market integration through time is maintained in all of these papers.

Carrieri, et al. (2001) combines the hypotheses mild-segmentation in international financial markets, which were developed in separate papers by Errunza and Losq (1985), Errunza and Losq (1989) and Errunza, et al. (1992)[98]; with the time-varying measure of integration developed in BH. The thrust of the method is to

[97] A regime or markov switching model is a method of modelling time series with changes in regimes. It estimates probabilities of times series that move from one state or regime to the other. These states are normally independent and unobservable and are governed by different time series in each state. These times largely due to the work of Hamilton (1989). A textbook analysis is provided in Hamilton (1994b).

[98] In these models, the polar cases of segmentation or integration are not assumed.

utilize the Errunza and Losq (1985) model to develop a mean equation in the context of the time varying world market integration model of stock market integration developed by BH. The new model generates conditional variances in a GARCH-M framework but maintains the original ideas of both methodologies. The results suggest that the last decade has witnessed an increased level of integration among emerging stock markets. The method proposed in Hardouvelis, et al. (1999) is to use converging forward interest rate differentials as integration proxy in a BH-type framework. Thy find that European markets have become increasingly integrated in the last decade.

Another very recent approach to conditional asset pricing models is to individually map the time series dynamics of the various components of stock returns in order to understand the ex-post relationship between stock prices and fundamental variables. In an attempt to understand what has been described as the "volatility puzzle" – quantitatively equity prices are far too volatile to be justified as present value of fundamental cash flows – and, the "correlation puzzle" – present values restrict cross-correlations of asset returns[99], Bansal and Lundblad (2002) have tested the conditional CAPM (IAPM)[100]. By adequately modelling the times-series dynamics of cash flow growth rates and the rates of return (cost of capital) Bansal and Lundblad have been able to offer some new insights into equity market volatility and return cross-correlations. In particular, they have used specified time-series dynamics for each of the components of the conditional IAPM and have found supportive evidence for their structure. They estimated three different types of IAPM: a CAPM-GARCH with dividends, a CAPM-GARCH with earnings, and

[99] The correlation between asset returns is documented to be six times greater than for the cash flow growth rates.

a CAPM-latent stochastic volatility with earnings. Their evidence indicates that the interactions between the growth rate dynamics of cash flows and stock returns can justify the "volatility puzzle" and the "correlation puzzle"[101].

All the evidence in support of a conditional IAPM seems to suggest that international capital markets are integrated and that the restrictions imposed by this model are, to a very large extent, valid. This has implications for international portfolio investors especially for large institutional investors making international asset allocation decision. For example, when designing strategies for forecasting international stock returns, models with conditioning information set performs better than unconditional models [Solnik (1993)]. It is important, however, to note that, conditional asset pricing models with time-varying risk structures are themselves not a panacea to the problem of adequately price financial assets, although they do offer considerable improvements. In a series of tests of the models by Fama and French (1993) and Elton, et al. (1995); Ferson and Harvey (1999a) suggested that although the use conditioning information (time-varying betas) provides an improvement to the respective three-factor and four-factor models, there remains significant predictable patterns in the pricing errors of conditional versions of these models. This is a very important point because it has potential implications for investors wishing to forecast stock or bond returns. We will now examine the evidence for the International APT (IAPT).

[100] This notion of volatility and correlation is originally due to Campbell and Shiller (1987;(1988a;(1988b) amongst others. See Bansal and Lundblad (2002) and references therein.
[101] Although the use of an augmented CAPM in a dynamic volatility-type framework is not entirely new (see for example, Bollerslev, et al. (1988)and Engel and Rodriguez (1989)); what makes this study interesting is the 'compartmentalised' approach to modelling the time series behaviour of stock prices. The econometric exercise is very thorough and far-reaching indeed. This provides substantial (additional) information on the time series behaviour of the components of stock prices. We will not attempt to discuss them in detail here.

An alternative to the CAPM is the APT formulated by Ross (1976). Domestic tests of the APT, for example, Roll and Ross (1980), Chen, et al. (1986), Connor and Korajczyk (1988), Elton, et al. (1995) and Antoniou, et al. (1998) have generally revealed that the APT performs better than the CAPM, and that that there are more than one priced variable in the return generating process for domestic stock returns. How well does the APT perform for international stock markets? Tests of the APT in an international context have been conducted by, among others, Solnik (1983), Cho, et al. (1986), Gultekin, et al. (1989), Korajczyk and Viallet (1989;(1992), Mittoo (1992), Bansal, et al. (1993), Ferson and Harvey (1993, (1994), Korajczyk (1996), Ferson and Harvey (1997), Fama and French (1998), Ferson and Harvey (1999b) and Griffin (2002)[102]. The general finding is that tests of APT performs well for international stock markets and the APT outperforms the CAPM in describing the return generating process of international stock returns. Three main methods have been used to derive the factors in the APT. Factors have either been pre-specified, derived from asymptotic principal component analysis or factor analysis, or from a fundamental characteristic approach. In additions, conditional versions of the APT (factor models) have also been tested and this has been regarded as an improvement to the unconditional factor model [Ferson and Harvey (1997)].

The IAPT offers an improvement on the IAPM because in the IAPT, the return generating process of financial assets is characterised by multiple sources of risks. Solnik (1983) shows that if a factor structure holds when assets returns are expressed in some reference currency, then the factor structure is invariant to the reference currency; and the IAPT is valid. In other words, the exchange rates and

[102] All of these studies conduct tests of versions of the APT or a multifactor model, which is

stock returns must follow the same factor structure for the IAPT to be valid – investors are assumed to have homogeneous expectation: identical consumption and investment opportunity sets across countries. Cho, et al. (1986) were the first to expressly test the IAPT under the joint hypothesis that capital markets were integrated and the APT hold internationally. They used factor analysis to estimate common international factors (factor loadings) and cross-sectional regressions to test the pricing implications of the IAPT. Their results indicate a rejection of the joint hypothesis of market integration and the validity of the IAPT[103].

Gultekin, et al. (1989) found some supportive evidence for the validity of the IAPT and the integration of capital markets but this evidence is dependent on the levels of investment barriers (what the authors call "Government Impediments") that existed in a market. The IAPT, tested using both the well-known two-stage estimation approach formulated by Fama and MacBeth (1973) and factor analysis, was rejected during the periods of capital controls; but after the regime switch to liberalised markets (in the case of Japan – the 1980 Foreign Exchange and Foreign Trade Control Law) the test were unable to reject the hypothesis of integration and Japanese and American stocks were found to have identical risk premiums. Korajczyk and Viallet (1989) conducted extensive tests of both the domestic and international versions of the CAPM and APT. They test the IAPT using the asymptotic principle component technique of Connor and Korajczyk (1986) to estimate the pervasive factors. In general, Connor and Korajczyk find that the APT (multifactor models) outperforms the CAPM when one uses a value-weighted portfolio although; the equal-weighted CAPM performs about as well as the APT. In an international context, after controlling for regime shifts in the levels of

equivalent to the APT.

investment restrictions [as done in Gultekin, et al. (1989)] , the International CAPM (IAPM) outperforms the domestic CAPM but, surprisingly, the IAPT does not outperform the domestic APT. There was some evidence against the validity of all the models they were investigated. In a related analysis, Korajczyk and Viallet (1992) examined the relationship between the structure of risks in international equity markets (stocks) and forward foreign exchange markets (forward contracts) using the APT with time-varying betas – a conditional APT model. They were unable to simultaneously price forward contracts and equities – forward contracts have a component of their conditional mean returns unexplained by their relation to equity factors. In other wards, the return generating process for forward contracts is not identical to those for equities. This has some implication for international investors wishing to hold a perfectly hedged portfolio that is hedged for foreign exchange risks.

In addition to the use of the unconditional and conditional IAPT, Bansal, et al. (1993) have suggested the use of a non-linear version of IAPT in explaining the time series behaviour of international asset returns because of the possibility that payoffs of financial assets might follow a non-linear factor structure[104]. They suggest that with such structure for the IAPT, offers an improvement in simultaneously pricing returns in bonds and foreign currency markets. The non-linear IAPT also out performs the unconditional and conditional linear IAPT although they also perform fairly well. Interestingly, Bansal et. al. noted that their test for an additional factor does not reject the one factor model. This makes their results consistent with earlier evidence, notably, Solnik (1974b) and Harvey (1991). Other tests of the IAPT include the work by Korajczyk (1996) which

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[103] They suggest that markets could be integrated for a subset of countries or regions.

examined the evidence of market integration in mature (developed) and emerging markets. Korajczyk used the IAPT to measure capital market integration in the context of the Law of One Price (LOP) hypothesis and the deviations from the LOP. The IAPT is well suited to this type of test because it can identify risks that are important and common to international investors and its structure allows for the measurement of deviations (or pricing errors in the IAPT) from the LOP through the vector of intercept terms in model. His results indicate the levels (which tends to decrease through time) of market segmentation – deviations from the LOP or pricing errors in IAPT – are larger for the emerging markets than for developed markets.

Another approach to testing the IAPT is the fundamental characteristic approach suggested by Fama and French (1998)[105] [FF98]. FF98 approach to testing their two-factor model or APT is equivalent to tests of the APT that used pre-specified factors; as done for example in Antoniou, et al. (1998) who specified some macroeconomic factors to test the validity of the domestic APT for the UK stock market. FF98 were extending their groundbreaking work on the domestic CAPM and other multifactor models to international stock markets. Specifically they were looking at the international evidence on value and growth stocks. The definition of value and growth in this study depends on fundamental characteristic variables[106]. Assuming that capital markets are integrated and allowing for deviations from PPP, FF98 test the two-factor ICAPM or APT (IAPT) with the global market return and international relative distress the two factors[107]. FF98 conduct an unconditional test

[104] The structure of the non-linear IAPT is due to Bansal and Viswanathan (1993)
[105] The models in this paper is based on earlier studies by the same authors: Fama and French (1992, (1993, (1995, (1996)
[106] See note 81 above for definitions of value and growth stocks.
[107] Relative distress refers to the value premium. Ibid.

of the IAPT and provide supportive evidence for the validity of their two-factor IAPT or ICAPM. It was also shown that the IAPT performs better than the international CAPM (IAPM) in explaining the returns on value portfolios. In other words, the value premium (relative distress) is pervasive. FF98 also found similar evidence for emerging markets.

The debate between academics and practitioners is whether lagged fundamental characteristic variables (which practitioners favour) or classic macroeconomic factors (apparently favoured by academics) describe financial asset returns better. Ferson and Harvey (1997) attempt to offer unifying theme by testing both fundamental characteristic variables – such as price-to-book-value (or book-to-market) ratios – and classic macroeconomic variables – like relative GDP per capita – in a conditional two-factor IAPT framework[108]. Their results indicate that the price-to-book-value ratio significantly affects global stock markets. In general, Ferson and Harvey suggest that international asset pricing models that do not account for relevant fundamental characteristic variables (or attributes) are mispecified. It also important to note that since tests of asset pricing models which utilises fundamental characteristic variables are based on the grouping of portfolios on the basis of the chosen fundamental variable – as in Fama and French (1998) for example; the grouping method could potentially affect inferences obtained from tests of these models. Ferson, et al. (1999) suggests that the grouping can significantly affect the inferences obtained except when these characteristics or attributes are chosen following an empirically observed relation to the cross-section of stock returns. Berk (2000) have also suggested that the grouping of data for asset

[108] Conditional here is equivalent to an instrumental variables approach!

pricing tests introduces a bias which could lead to the incorrect rejection of an asset pricing relation.

Griffin (2002) explores the validity of Fama and French (1993) three factor model for international stock returns. The three factors in the model are the market return, the size factor, and the book-to-market equity factor. Compared to the international equivalents of these factors, Griffin suggests that domestic (country-specific) versions of the three-factor model outperform the world three-factor model. This results is surprisingly similar to those reported by Korajczyk and Viallet (1989), for the APT and IAPT. There was, however, some improvement in explanatory power when domestic three-factor models were augmented by foreign factors. This finding has important implications for practitioners who use assets pricing models for calculating for example, the cost of capital in capital budgeting projects. In effect, the size of the mispricing (pricing errors) would depend on the version of the model used.

Other multifactor models that have been used in tests of capital market integration are what are known as latent variable models or unobservable factor models. Bekaert and Hodrick (1992), Campbell and Hamao (1992) and King, et al. (1994)are indicative examples of empirical research that uses latent variable models in tests of capital market integration. In chapter 5, we estimate a latent factor model for international equity and bond markets. Our new methodology follows the approach of King, et al. (1994) amongst others[109].

[109] Further details provided in chapter 5.

Continuous-time finance models and intertemporal or consumption-based asset pricing models have also been used in studies capital market integration. A continuous-time version of the IAPM is presented in Stulz (1981) and Adler and Dumas (1983). Wheatley (1988) estimates a simple version of the traditional consumption-based asset pricing model, which relates a representative individual's expected real return on each asset to the covariance of this return with growth in the individual's real consumption, in a cross-country framework. Two consumption models are estimated. One incorporates barriers to international investments and the other does not. The individual is allowed to hold both domestic and foreign goods in their portfolios[110]. According to Wheatley, "the tests provide little evidence against the joint hypothesis that equity markets are integrated internationally and the asset pricing models holds".

The approaches taken in Stulz (1981) and Adler and Dumas (1983) are very similar. They allow for both stochastic inflation in each country and for the deviations from PPP. Adler and Dumas (1983) define the dynamics of price level changes in each country using Brownian motion. They assume that investors face a constant investment opportunity set. Stulz (1981) also using Brownian motion (stochastic differential equation) defines the dynamics of goods prices in a model which recognises that there are cases where the law of one price holds for all goods; for example price indices would be different across countries because of differences in tastes; and there are cases where PPP does not hold due to the nature of the good, being that it is not traded internationally[111]. Basak (1996) has also developed a theoretical intertemporal model of capital market segmentation. The

[110] We do not intend to describe this model in full here. We will concentrate on the continuous-time models instead

[111] The specification of these models are based on the seminal work of Merton (1973)

model extends the standard international mean-variance to incorporate intertemporal consumption and endogenous interest rates. We will only discuss the model Adler and Dumas (1983) in some detail. This model is widely regarded as the basis for most of the other continuous-time finance models in international asset pricing studies.

Briefly, Adler and Dumas (1983)[112] considers a world of L + 1 currencies. Measures nominal returns in terms of the L + 1st currency where, the nominal rates of return given in another currency can be easily translated by multiplying one plus the foreign-currency rate of return by the ratio of the end-of-period to the beginning-of-period exchange rates. They assume that there are N nominally risky securities, whose nominal price dynamics in terms of the measurement currency are given by stationary Ito processes (Brownian motion):

$$\frac{dY_i}{Y_i} = \mu_i dt + \sigma_i dz_i \quad i = 1 \cdots N \tag{2.3}$$

Where Y_i is the market value of security i in terms of currency L+1, μ_i is the instantaneous expected nominal rate of return on security i, σ_i the instantaneous standard deviation, z_i is a standard Wiener process and dz_i is the associated white noise. The instantaneous covariances, σ_{ik}, of the nominal on the various securities is defined as $\underline{\Omega}$, an $N \times N$ matrix[113]. The N + 1st[1] asset is nominally riskless, for example, an interest earning bank deposit or short term bond denominated in the measurement currency. The instant nominal interest rate paid on this deposit is denoted by r. The last L securities are the nominal bank deposits denominated in the non-measurement currencies and the first $n (n = N - L)$ are stock securities

[112] The discussion here is based on Adler and Dumas (1983) and we have maintained their notations and descriptions throughout.

paying a random dividend. There are also, L + 1 national investor type, each with homothetic utility functions[114]. The price index P^l of investor type l, expressed in measurement currency, follows the following stationary process:

$$\frac{dP^l}{P^l} = \pi^l dt + \sigma_\pi^l dz_\pi^l \qquad l = 1 \cdots L+1 \tag{2.4}$$

π^l and $\underline{\sigma_\pi^l}$ are the expected value and standard deviation of the instantaneous rates of inflation as seen by investor of type l. The covariances $\sigma_{i,\pi}^l$ of the N risky securities returns with investor $l's$ rate of inflation is defined as $\underline{\omega}$, an $N \times N$ vector of covariances.

In summary, the model proposed by Adler and Dumas (1983) has constituted the basis for studies of continuous-time models of international integration. In discussions about the home bias puzzle for example, it is noted that most of the models that attempted to describe the puzzle in terms of the hedging of purchasing power risks actually used the Adler and Dumas model as the basis of their study. A continuous-time IAPM with time-varying expected returns was also suggested by Hodrick (1981) in his study of forward premium in the foreign exchange market. All of the different types of IAPM's can be regarded as special case of the ICAPM derived by Merton (1973).

2.4 General Financial Econometric Time Series Approach to Modelling International Capital Market Integration – Cointegration, causality, lead/lag relationships and volatility transmission models.

There have been many studies of capital market integration from a financial econometric time series perspective. We do not attempt to review all of these here.

[113] If partitioned correctly, the southeast block of the covariance matrix contains the covariance of exchange rates (Adler and Dumas (1983)).

The literature reviewed here is very much related to most of the key issues discussed in the previous sub-sections. In this regard only a general summary is provided. Detailed analysis will be given in the relevant empirical chapter where appropriate.

Cointegration techniques have been widely used to assess capital market integration. One of the first studies to apply Engle and Granger (1987)[115] cointegration techniques in these studies was Taylor and Tonks (1989). They investigated the extent to which the UK stock market was integrated with international equity markets after the abolition of UK exchange controls in 1979. The cointegration test reveals a strong long-run relationship between the UK and international markets post-1979[116]. Eun and Shim (1989) conducted a more detailed VAR analysis using innovation accounting methods – impulse response analysis. Their results suggest that innovations in the US stock markets are rapidly transferred across international markets. The converse was not true[117]. Phylaktis (1999) conducted a similar analysis for the Pacific-Basin countries examining the leading role of the Japanese stock market using impulse responses analysis of a cointegrated VAR model as suggested by Lutkepohl and Reimers (1992). Kasa (1992) extended the cointegration technique in tests of market integration to extract common stochastic trends across international equity markets[118]. Common stochastic trends are a factor decomposition of estimated cointegrating vector into a

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[114] General and specific types of this function are defined in Adler and Dumas (1983). Because of space we do not reproduce this function.
[115] The Engle and Granger cointegration methodology has become standard in the academic literature. We do not review it here. Enders (1995) gives a concise review of cointegration.
[116] Similar cointegration tests using basic Engle and Granger methodology was conducted by Clare, et al. (1995) in their of the integration of international bond markets.
[117] A potential criticism of this paper is that is that the authors used daily data. Although their result is explained in this context, the original data may have distorted the analysis.

permanent and a transitory component[119]. Kasa's results indicate that a single common stochastic trend is responsible for the long-run comovements in international equity markets and he implied that the benefits of international diversification might have been overstated. Garrett and Spyrou (1999) found evidence of common trends in emerging markets but argue that there are still long-run benefits to international diversification. The multivariate technique of extracting common stochastic trends is conceptually related to the volatility transmission (spillover) question addressed below. Indeed, the presence of common stochastic trends in national stock markets can be viewed as a potential or an avenue for volatility transmission between these markets.

Simple causality tests suggested by Granger (1969)[120] have been used to examine the predictive ability stock markets. Malliaris and Urrutia (1992) conducted Granger causality tests[121] for six international equity markets. No lead-lag relationships were detected before the 1987 stock market crash. During the month of the crash there was a mixed lead-lag or feedback relationship between the markets. Causality tests from Taylor and Tonks (1989) were more clear cut suggesting that UK led the German, Dutch and Japanese stock markets after the abolition of UK exchange controls. Malliaris and Urrutia (1996) conducted cointegration analysis for European stock markets found evidence of cointegration

[118] The cointegration technique used in this study is the maximum likelihood approach suggested by Johansen and Juselius (1990) and Johansen (1991). Harris, et al. (1995) also used Johansen's technique to study long-run relationship between stock markets across the US.

[119] The decomposition used here is based on the methods suggested by Stock and Watson (1988). Common stochastic trend analyses have also been used to study a number of other issues in finance. Luintel and Paudyal (1998) for example examined the relationship between a number of currencies using common trend analyses.

[120] This is a simple F-test of a restricted equation to assess predictive ability of a time series process.

[121] This test is defined in Granger (1969) or any standard intermediate or advanced econometrics textbook

with valid error correction model[122]. Causality test have also been applied to cross-listed stocks to price discoveries (lead-lag relationships). Eun and Jang (1997) investigated the relationships between cross-listed stocks in the London, New York and Tokyo stock exchanges using a vector error-correction model (VECM)[123]. They show that innovations in the home market of the cross listed stocks are fed back (Granger causes) into the cross-listed market. This evidence suggests the existence of a transmission mechanism (spillover) in financial markets especially second moments (volatility) transmissions.

Issues relating to volatility transmission across international financial (equity) markets have been actively investigated in the academic literature. A number of authors including for example, Eun and Shim (1989), King and Wadhwani (1990), Engle, et al. (1990a), Ng, et al. (1992b), Theodossiou and Lee (1993) and King, et al. (1994). We also noted several contributions in this area in our discussions of the relationship between volatility and correlation and, the correlation structure of international equity returns in previous sub-sections. The stock market crash of 1987 motivated a majority of the research in this area. Generally, the spillover question has been addressed from a bivariate conditional second moment (volatility) modelling framework. Engle, et al. (1990a) applied a GARCH model to test volatility transmission in daily exchange rate across Japanese and US foreign exchange markets. The basic idea is to model the conditional mean or the conditional variance of one market as a function of the conditional mean or conditional variance of the other market. Evidence of volatility spillover suggests market interdependence. Engle, et al. (1990a) used volatility-type VAR model for

[122] Other studies that have used cointegration analysis to study the dynamic relationships between international equity markets include Abbott and Chow (1993), Masih and Masih (1997) and Ratanapakorn and Sharma (2002). All of these studies used Johansen's VECM approach.

their GARCH specification. For equity markets, Hamao, et al. (1990) used a similar framework – a GARCH(1,1)-in-Mean with cross moments included – to characterise volatility spillovers across the three of the worlds largest equity markets using daily and intraday returns. They document evidence of volatility spillovers from the US and UK markets to the Japanese stock market.

Volatility transmissions can also be asymmetric and have differential impacts. Volatility transmission could be more pronounced for bad than for good news. To this end, Koutmos and Booth (1995), Koutmos (1996), Booth, et al. (1997), Koutmos (1998) used multivariate asymmetric volatility models with cross moments terms to investigate the transmission of volatility across international markets. All of these suggest both price and volatility spillover across international markets, and a differential impact of volatility transmitted – negative innovations from one market having larger impact upon the volatility of another market than equivalent positive innovations especially for those markets that operates in different time zones.

Other approaches to measuring volatility transmission include the method rational expectations approach suggested by King and Wadhwani (1990) in which agents do not assess the economic implications of news from an overseas market for themselves but simply, respond by 'shooting first and asking questions later (Shiller, et al. (1991)). Shiller, et al. (1991) used a survey questionnaire approach. They asked Japanese institutional investors various questions surrounding the events of the stock market crash of 1978. They found that the primary concern of these investors was news emanating from the US upon which they acted. Lin, et al.

[123] A VECM is a VAR representation of a cointegrated system.

(1994) viewed the volatility transmission question as a signal extraction problem. In their model, agents in a local market have to extract both the global and local component from any news event. The methodologies we develop in Chapter 5 a similar methodology in the stage of our analysis.

The literature has also included studying transmission mechanism between different asset classes. Antoniou, et al. (2003) is a significant contribution in this area. They[124] looked at the relationship between stock indices and the futures on these indices across a number of EU countries. They used a multivariate VAR-EGARCH model to the volatility transmission and lead-lag relationships between these markets. Their results indicate a substantial transmission and lead-lag effects within and between French, German and UK stock markets. This is a particularly interesting strand in the literature especially for international financial stability purposes. Authorities in central banks and other financial regulatory bodies are interested in cross-asset market dynamics in order prevent financial crises in the form of financial instability and financial contagion. Knowledge of how the equity markets reacts to the stock index futures markets would be very useful for financial stability officials.

Another related issue in this literature is whether or not capital market integration or liberalisation increases financial market volatility. Some have (in development economics; see for example Hassler (1999)) suggested that financial integration increases domestic stock market volatility through various transmission mechanisms. The evidence from financial economics suggests otherwise. Volatility estimates from conditional second moments models, for example De Santis and

[124] This paper was first circulated as a CERF working paper in 2001 as Antoniou, et al. (2001).

Imrohoroglu (1997) and Huang and Yang (2000) and event study analysis, in for example Kim and Singal (2000b) and Kim and Singal (2000a) suggest that liberalisation does not increase volatility. Liberalisation actually in creases returns and may reduce volatility. Similar evidence have been reported in Bekaert and Harvey (1997) and Ng (2000) in their examination of the changing nature of volatility spillovers. The volatility spillover models used in these studies nests both the conditional second moment approach and event study methodology.

2.5 Economic integration, stock market integration and stock market development

The stylised facts presented so far suggest that financial economists have made tremendous advances in measuring the deviations from the law of one price in international financial markets and have continued to assess market interrelatedness from different perspectives. Other issues that have also received some attention in the academic literature include the relationship between economic growth and market integration and, between stock market development and market integration. There is also a large literature on links between economic growth and financial development[125].

The relationship between the local financial market and the real economy is well established. There are results from Fama (1981, (1990), Chen, et al. (1986), Fama and French (1988) and Flannery and Protopapadakis (2002) which suggest that real activity explain some of the variation in equity market returns especially at longer horizons[126]. International evidence is found in Asprem (1989) who looked at the

[125] Levine (1997) provides a synthesis of these issues.
[126] Notable exceptions to this line of thinking include Mayer (1989)and Stiglitz (1989) who suggests that the existence of stock market has little relevance to real activity.

relationship between the financial market and the real economy in a number of European countries and documents evidence of a strong correlation between changes in stock prices and measures of real activity such as future industrial production and exports. Levine (1991) also provides strong evidence of the relationship between stock markets and economic growth and suggests that stock markets accelerate growth by creating secondary markets for the exchange and trade of ownership of firms and for providing an avenue for portfolio diversification. This analysis has recently been extended to include the effects of increased inter-linkages between financial markets on domestic economy[127].

From an international perspective various strands have been highlighted including the links between stock returns and macro variables such inflation, GDP and interest rates or the reactions of the local stock markets to different monetary policy regimes. For example, Cheung and Ng (1998) used multivariate cointegration techniques to examine the long-run relationship between aggregate stock market activity and aggregate real activity – measured by real oil prices, real consumption, real money and real output – in five international stock markets. Their result suggests evidence of long-run relationship between the stock market and the real economy. Wongbangpo and Sharma (2002) found evidence of a long-run relationship and 'Granger causality' between the real economy and the stock markets for a group of emerging markets. Kleimeier and Sander (2000) looked at the evidence for the integration of lending rates – in the context of an interest rate parity analysis – across EU countries to measure economic and financial market integration. They employed a cointegration technique which allows for structural

[127] Khalifa Al-Yousif (2002) provides evidence of bidirectional causality between stock market development and economic growth but cautions that this relationship must not be generalised across all countries.

breaks but failed find convincing evidence of economic integration across these markets and calls for regulation to increase financial market integration.

The relationship between economic and stock market (financial) integration have also been studied using variance decomposition (a VAR-type model) framework originally suggested in Campbell (1991) and extended by Campbell and Ammer (1993)[128]. In this framework, the interactions between news about expected returns and news about dividends is captured in a multivariate context by analysing the covariance structure of excess stock returns. Returns and return variances are decomposed into news about expected returns and dividends using innovation accounted methods. Ammer and Mei (1996) used this methodology to study economic and financial integration by analysing the covariance structure of excess returns in US and European stock markets. They decomposed unexpected stock returns into news about dividend growth rates, real interest rates and excess stock returns. Since the news variables are driven by fundamental economic events, this framework is well suited to studying economic and financial integration. Divided growth rates for example are closely related the long-term GDP growth rates. Understanding the nature of shocks and shock transmission between financial markets is therefore vital to understanding financial and economic convergence. Phylaktis and Ravazzolo (2002) used a similar analysis in their analyses of covariance structure excess returns in the Pacific-Basin financial markets. They find that 'financial integration is accompanied by economic integration'.

[128] This methodology was initially used to analyse the rational expectations versions of approximate present value model in Campbell and Shiller (1988a) which was rewritten in terms of unexpected and abnormal returns.

Others have also looked at the flow of goods across countries – capital mobility. Generally if capital is perfectly mobile across a number of countries and the capital markets of these countries are integrated, this suggests that there is both economic and financial integration across these countries[129]. Chen and Zhang (1997) for example, show that that the correlations of international stock returns reflect the economic ties between countries. Imperfect mobility of goods should not however be viewed as an impediment to financial integration. Dumas and Uppal (2001) show that the welfare gains from international financial integration are not significantly affected by imperfect mobility of goods – modelled as the cost of transferring goods from one country to the other – because trade in financial services are sometimes close substitutes for trade in goods across countries. Segmentation in goods would not necessarily reduce the benefits from international portfolio diversification.

Bekaert and Harvey (1995) noted that there is a strong interest in development economics for models that relate capital market restrictions and the stage of financial market development to economic growth. Indeed, Pagano (1993), Levine and Zervos (1996), Bekaert and Harvey (2000), Beck, et al. (2000) and Bekaert, et al. (2001)[130] have all found evidence suggesting a strong relationship between financial market development (integration) and real growth. Levine and Zervos (1998a, b) have also examined this relationship using asset pricing theories and found that the measure of mispricing in the IAPT is negatively correlated with

[129] There is a huge literature in international economics which address this question. We do not attempt to review those here. See Frankel (1992) for a review of these concepts and Krugman and Venables (1995) for some critical thoughts.

[130] This evidence is not entirely new. Goldsmith (1969), McKinnon (1973) and Shaw (1973) provided empirical evidence suggesting a positive correlation between financial development and economic growth. This strand of the literature is rapidly developing. Excellent reviews for this sort of analysis are provided in Demirguc-Kunt and Levine (1996a, b) and Demirguc-Kunt and Maksimovic (1998) amongst others.

economic growth. Bayoumi and MacDonald (1995) on the other used consumption patterns across countries to measure capital market integration. They find that real interest rates are not equalised across countries and that Japan was the only country for which national consumption was fully integrated with the rest of the world for the period 1973-92. Frankel (1992) provides evidence which supports a strong link between relaxing the barriers to international capital mobility and increased international financial integration[131]. Chang (1997) and Edison, et al. (2002) are notable exceptions to the developing consensus of a strong relationship between financial integration and real growth. Chang (1997) for example, suggest that financial integration can only be successful if governments agree to coordinate their macroeconomic policies; while Edison, et al. (2002) fail to establish that financial integration accelerate economic growth despite using a new and comprehensive list information variables. This has particular implications for international economic groupings such as the euro area. A similar criticism has been put forward by Oxelheim (2001), who espoused a new way of measuring complete financial market integration – the absence of capital controls; the efficiency of internal regulations , the absence of tax wedges and prohibitive transaction costs; exchange of information and the absence of cross-border information asymmetries, including differences between corporate governance systems and information costs – and assess this through the complex interplay between politicians, investors and managers.

Dellas and Hess (2002) also reports evidence from a VAR analysis which suggests that financial market development makes domestic markets more sensitive to

[131] There are several definitions of capital mobility. We do not explore these issues here.

external shocks even where markets are integrated[132]. Obstfeld (1998) stresses the need for stronger economic integration in order to achieve the full benefits of international financial integration. This issue is addressed in chapter 4 of this thesis. Similar views were expresses in Christoffersen and Errunza (2000) who noted that new global financial architecture with mobility of capital across international markets must address the risk management implications of modern methods of international finance in order to prevent international financial crises. Issues relating to financial innovation, high frequency financial data and real-time data analysis must be incorporated in assessing international financial market commonalities.

A counter argument from a purely macroeconomic point of view is suggested in Heathcote and Perri (2002) who noted that international economies have become more regionalised – "real regionalisation" – the correlations of GDP, employment and investments between the US and other industrialised nations have decreased considerably since 1987 although US international trade has substantially increased. There has also been a decline in the correlations of real shocks. The authors propose a model in which international financial market integration occurs endogenously in response to less correlated shocks. They suggest that the decline in correlation of real shocks increases the equilibrium level of portfolio diversification. The magnitude of this increase is the measure of financial market integration. The hypothesis here is that an increase in portfolio diversification arising in equilibrium further reduces the international correlations of output employment and investment. According to the authors, this explains the observed

[132] Hassler (1999) also suggests that increased financial integration would increase stock market volatility but evidence in for example, De Santis and Imrohoroglu (1997) suggests that volatility (in emerging markets) sometimes decreases with liberalisation.

changes in international business cycles. Heathcote and Perri (2002) results was based on calibration of a model of stock trading. When stocks are traded internationally subject to certain frictions which limits-risk sharing, the above hypothesis holds otherwise it does not.

2.6 Conclusions

This chapter has presented a comprehensive review of the theoretical framework of the key issues in international capital market integration. The review is by no means complete but has provided a taxonomic synthesis of the relevant issues for ideas developed in this thesis. We have examined the developments in theory of international portfolio diversification including the home bias puzzle, the expanding literature on international asset pricing, volatility and correlations in international financial markets, and the relationship between financial integration and economics integration. The evidence largely suggests that financial market have become more integrated but not perfectly integrated. The review also suggests that the correlation structure of international asset returns is time-varying and that time-varying volatility methods performs reasonably well in describing the transmission mechanisms between different assets and markets. Mixed evidence was obtained about the relationship between capital market integration and real macroeconomic variables.

In the next three chapters we conduct empirical analysis and develop new ideas about the lead-lag relationship between equity markets, the relationship between financial integration and economic integration, the comovements in equity and bond markets, and volatility structure and volatility transmission across international equity markets.

Chapter 3

Another look at the Economic Determinants of Evolution in Stock Market Integration: A European perspective

3.1 Introduction

In integrated capital markets we expect assets with identical risk characteristics that are quoted in different markets to have identical returns. In a loose sense the law of one price must hold for all identical securities. Chapter two provided various definitions of capital market integration and the nature of barriers to international investments. One of the approaches adopted by financial economists studying international capital market integration is to assess the extent to which financial markets influence each other. To describe influence we examine the nature of interdependencies and/or the lead/lag relationship between financial markets. Koch and Koch (1991) suggested that regional interdependencies between financial markets have grown considerably. In fact, in the immediate aftermath of the stock market crash of October 1987 a large number of academics and practitioners turned their attention to understanding the interdependencies and co-movements that exits between international stock markets[133]. Roll (1988a) used both univariate and multivariate analysis to assess the effects of both institutional characteristics and worldwide market movements. Eun and Shim (1989) studied the dynamic effects of price changes in nine stock markets. King and Wadhwani (1990) used a rational expectations model to interpret the transmission of volatility between stock markets with dissimilar macroeconomic conditions. Hamao, et al. (1990) found some evidence of short-term price and volatility transmission between international markets. Malliaris and Urrutia (1992) assessed the lead-lag relationships between six major stock markets. Antoniou and Garrett (1993) investigated the extent to which stock index futures trading contributed to the crash and, Antoniou, et al. (2001) investigated the transmission mechanism between the stock index and stock index futures markets.

Despite this increase in research at the time, the international asset pricing literature had actually evolved for over a decade with issues relating to the integration and segmentation of stock markets characterising the key stylised facts[134]. Researchers initially focussed on testing the unconditional Capital Asset Pricing Model (CAPM) and the Arbitrage Pricing Model (APT) in an international context but these were fraught with difficulties[135]. Recently the focus has shifted to conditional test in which expected returns and risks are permitted to vary over time. Bekaert and Harvey (1995), Dumas and Solnik (1995) and De Santis and Gerard (1997) are examples of conditional tests of international asset pricing models which have specifically addressed issues of market segmentation and integration.

In this chapter we study capital market integration or interdependence by examining the levels of linear dependence and feedback between pairs of markets[136]. We use 'the econometrically elegant' measures of linear dependence and feedback between multiple time series developed by Geweke (1982) to study the extent of capital market integration between European countries. We also

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[133] Roll (1989) surveys the immediate theoretical and empirical explanations put forward.
[134] See for example Solnik (1974a), Black (1974), Subrahmanyam (1975), Stapleton and Subrahmanyam (1977), Grauer, et al. (1976), Stulz (1981a), Errunza and Losq (1985), Eun and Janakiramanan (1986), and Hietala (1989). Chapter 2 provides an extensive survey of the theoretical framework of capital market integration.
[135] These issues were discussed in chapter 2
[136] Since we are only employing a pair-wise analysis, cross-country correlations are implicitly excluded. However we report results from the bilateral relationship between seventeen countries, enough information would be available to conjecture or speculate on the likely outcome for a cross-country analysis. Cross-county analysis is left for future research.

employ a dynamic panel data analysis to assess the economic determinants of the measures of integration. Our approach to testing for stock market integration is similar to the one adopted by Bracker, et al. (1999) [henceforth BDK] but we offer an improvement. The BDK methodology was also due to Geweke (1982). Unlike BDK we use dynamic panel data (DPD) techniques suggested by Arellano and Bond (1991), Arellano and Bover (1995) and, Blundell and Bond (1998) to understand the relationship between financial integration and macroeconomic convergence. This specification allows us to unlock the dynamics of capital market integration and economic integration and in particular, to study the time-varying nature of stock market integration. We look at the relationships between our measures of capital market integration and the following macroeconomic variables: the short-term real interest rate differential, the inflation differential and the rate of change in the nominal exchange rates between any two countries.

These three measures, together, constitute deviations from purchasing power parity (PPP) and interest rate parity (IRP) between the countries. Deviations from these parity conditions would influence the extent of bilateral trade and capital flows between the counties. Increases or decreases in bilateral trade may be driven by economic integration. We expect that changes in these measure would have little on no impact on measures of capital market integration on the same day but more impact on measures of capital market integration across days because, deviations from PPP and IRP are likely to increase trade and capital flows between the countries[137]. Fieleke (1996) emphasised the importance of a shrinking interest rate and inflation differentials between countries in an integrated capital market.

[137]A similar approach is adopted in BDK. However, where PPP and IRP hold perfectly, it is possible that that there may be some double counting because our measures of economic integration may

However, it is important to note that financial and economic convergence between two countries does not necessarily mean a complete elimination of interest rate and inflation differentials between the countries. The relationship between our measures of integration and the selected macroeconomic variables [spreads] nevertheless gives the opportunity to understand the effects of the macroeconomy on the levels of capital market integration within the same day and across days.

Research on the interrelationships between capital markets has become more pertinent due to the increased globalisation of financial services and technological advancements in trades involving financial instruments. An understanding of the dynamics of regional financial interdependence is crucial for policy analysts and financial market regulators. Knowledge about the interrelationships and interactions between international stock markets would enable financial market participants to better prepare for events such as the 1987 crash or the more recent phenomena of blips, substantial blips and sustained blips that occurred in the mid 1990's due to the Asian financial crises and other similar crises and which keeps occurring as this thesis is being written.

Anecdotal evidence suggests that barriers to international investments are being dismantled. However, this casual observation of the reduction in the removal of capital controls across counties is not in itself sufficient evidence of capital market or economic integration. Indeed Bekaert and Harvey (2000) suggested that capital market liberalisation may not be enough to encourage foreign investors to actually invest in a country. The well-known Home Bias puzzle is just a case in point[138].

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pick up residual financial integration. Nevertheless, to the extent that these factors influence the measures of integration and are significant, we will be capturing substantial economic integration.

[138] See Bekaert (1995) for an excellent overview of the major barriers to international investments.

Tesar and Werner (1995) amongst others[139] provide evidence in support of investor home bias in the construction of investment portfolios despite the gains in international portfolio diversification.

Our focus here is to understand (in a European context), the evolution of contemporaneous integration and the lead/lag relationships between financial markets[140]. Europe is a very important trading block in international economics terms and it hosts three of the top five economies in the world. The collection of countries with close trade links such as those in the European Union (EU) and its closest free trade partners provides an ideal setting to study capital market movements and interdependencies and, how this relates to economic convergence. Also, improving our understanding of the macroeconomic determinants of financial market interdependence is crucial to the success of the new international financial architecture. Knowledge of the links between real macroeconomic activity and financial integration would allow both policy makers and international investors to successfully manage the evidently growing international financial interdependence. In a recent paper Errunza and Hogan (1998) found that for many European equity markets, return volatility predictions can be enhanced by incorporating information about the macroeconomy. In an earlier paper Fama (1990) suggested that a large fraction of the variation of stock returns can be explained, primarily by time-varying expected returns and forecasts of real activity. Hardouvelis, et al. (1999) used converging forward interest rate differentials, measured vis-à-vis Germany, as proxy for integration and conclude that European markets have increasingly become integrated and that those differentials are disappearing. It is therefore

[139] See also French and Poterba (1991) and Cooper and Kaplanis (1994) for further discussion on this issue.
[140] This terminology is due to Koch and Koch (1991).

important to discover the relationships between real activity convergence and financial market interdependence measured by the linear dependence and feedbacks between international stock indices.

Our study therefore contributes to the growing literature on time varying international stock market integration and international capital market efficiency. We also contribute to the debate on whether international stock market movements are driven by converging economic fundamentals.

We apply the Geweke methodology to 17 European stock markets – EU15 plus Norway and Switzerland. We find evidence of strong interdependence on the same day between the countries in our sample and a very patchy evidence of dependence or feedback across days suggesting that European markets react to each order very strongly on the same day but the effects of this information flow does not last beyond the 24 hour period. Our DPD analysis reveals strong evidence time varying integration for measures of linear dependence or same day integration but not for measures of feedback or integrations across days. Unlike BDK, we find that inflation differentials between the countries are strongly associated with levels of interdependence on the same day, and, the levels of bilateral exchange rate between the countries influence levels of integration or feedback across days. We did not find any association between the real short-term interest rate differentials and the levels of integration between any two countries in our sample. The rest of the chapter is organised as follows: section 3.2 we discuss the methodology and data, section 3.3 presents and discuses the empirical results and we conclude in section 3.4.

3.2 Methodology

Like BDK, we implement a two-step analysis in this chapter. In stage one we use Geweke's measures of linear dependence and feedback between multiple time series to unlock the contemporaneous (linear dependence) and lead/lag (unidirectional feedback) relationships between the markets. In stage two, unlike BDK who used a simple pooled regression, we use Dynamic Panel Data (DPD) methods suggested by Arellano and Bond (1991), Arellano and Bover (1995) and, Blundell and Bond (1998) to assess the strength of the relationship between our measures of integration and selected macroeconomic variable which influence the extent of bilateral trade relationship between pairs of countries in our sample. We will now discuss these methods in turn

3.2.1 Geweke's Measure of Linear Dependence and Feedback

The measures of linear dependence and feedback developed by Geweke (1982) and illustrated by Hamilton (1994b) are simply maximum likelihood estimation of restricted vector autoregressions (VAR). For our analysis we have employed a near-VAR[141] model for stock returns in estimating the bilateral relationship between the 17 countries in our sample. A near-VAR model allows for different lag lengths on the right hand variables in a VAR. It also allows for the possibility of different right-hand-side variables in one or more equations in a VAR. We suggest the use the use of a near-VAR model because we hypothesize that national stock returns are influenced to a varying degree by: (i) past returns in another market, (ii) it own past returns, and (iii) noise.

The general model is represented by:

$$r_{1t} = c_1 + A_1' x_{1t} + A_2' x_{2t} + \varepsilon_{1t} \quad \mathrm{var}(\varepsilon_{1t}) = \Omega_{11} \qquad (3.1)$$

$$r_{2t} = c_2 + B_1' x_{1t} + B_2' x_{2t} + \varepsilon_{2t} \quad \mathrm{var}(\varepsilon_{2t}) = \Omega_{22} \qquad (3.2)$$

$$\text{with cov } = E\begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} = \begin{bmatrix} \Omega_{11} & \Omega_{12} \\ \Omega_{21} & \Omega_{22} \end{bmatrix} = \mathrm{Y}$$

Where r_{1t} and r_{2t} are (n_1 x 1) and (n_2 x 1) vectors of the stock returns of say for example country 1 and country 2 respectively, x_{1t} and x_{2t} are (n_1p_1 x 1) and (n_2p_2 x 1) vectors of lagged returns of countries 1 and 2 respectively with p_1 and p_2 representing the lag truncation parameter, c_1 and c_2 are (n_1 x 1) and (n_2 x 1) vectors of constant terms. The matrices A_1, A_2, B_1, and B_2 contain the autoregressive coefficients. Y is the variance-covariance matrix of the system in (3.1) and (3.2) and we allow for contemporaneous correlation between returns. We assume that the error terms ε_{1t} and ε_{2t} are Gaussian, distributed $N(0,\Omega_{i,j})$, [for $i = 1, j = 1; \& \ i = 2, j = 2$] and, not autocorrelated.

To estimate the bilateral relationship between the stock returns of any pair of countries in our sample we test the following three hypotheses:

H_1: There is no contemporaneous relationship or integration between market 1 and market 2 on the same day

H_2: Market 2 does not lead market 1 across days (no feedback emanating from market 2 across days)

[141] This terminology is the one adopted in Enders (1996). Although we are using a near-VAR

H_3: Market 1 does not lead market 2 across days (no feedback emanating from market 1 across days)

To test the above hypotheses, we have to subject the system in (4.1) and (4.2) to the following block exogeniety tests:

$$r_{1t} = c_1 + A_1' x_{1t} + \mu_{1t} \quad \text{var}(\mu_{1t}) = \Omega_{\mu 11} \qquad (3.3)$$

$$r_{2t} = c_2 + B_2' x_{2t} + \mu_{2t} \quad \text{var}(\mu_{2t}) = \Omega_{\mu 22} \qquad (3.4)$$

$$\text{with cov} = E\ (\mu_{1t} \mu_{2t}) = 0$$

Effectively, we are setting the coefficients in the matrices A_2 and B_1 equal to zero to test the restriction imposed by our block exogeniety tests. We unlock the bilateral relationship between any two countries by hypothesizing that the lagged values of the returns of one country does not to help to forecast the returns in the other country. To test the restrictions imposed by (3.3) and (3.4) Geweke (1982) assuming Gaussian error terms suggested the following likelihood ratio statistics which are equivalent to the quasi-maximum likelihood estimates for the validity of the restrictions imposed:

1. To test linear dependence or the hypothesis (**H_1**) of no contemporaneous relationship between the returns of country 1 and country 2 we use the following likelihood ratio statistic

   $$T \left\{ \log \left| \hat{\Omega}_{\mu 11} \right| + \log \left| \hat{\Omega}_{\mu 22} \right| - \log \left| \Upsilon \right| \right\} \qquad (3.5)$$

   Where T is the number of observations and the other variables are the log determinants of the variance and variance-covariance matrices in (3.1) –

model, in the original Geweke paper, the VAR can be of any specification.

(3.4). We use this test statistic to determine the contemporaneous relationship between the pairs of markets in our sample. This statistic has a χ^2 distribution with $(n_1 n_2)$ x (2p +1) degrees of freedom[142].

2. The statistic in (3.5) can be decomposed in three feedback measures two of which are used here as follows:

   a. Measures of linear feedback from country 2 to country 1 as

$$\hat{F}_{2\to 1} = T\left\{ \log\left|\hat{\Omega}_{\mu 11}\right| - \log\left|\hat{\Omega}_{11}\right| \right\} \qquad (3.6)$$

This statistics is distributed χ^2 $(n_1 n_2 p_2)$

We test the hypothesis in $\mathbf{H_2}$ that the return of country 2 does not lead the returns of country 1 across time (days).

   b. Measures of linear feedback from country 1 to country 2 as

$$\hat{F}_{1\to 2} = T\left\{ \log\left|\hat{\Omega}_{\mu 22}\right| - \log\left|\hat{\Omega}_{22}\right| \right\} \qquad (3.7)$$

This statistics is distributed χ^2 $(n_2\, n_1 p_1)$

We test the hypothesis $\mathbf{H_3}$ that the returns of country 1 does not lead the returns of country 2 across time.

In the equations (3.6) and (3.7) we are testing market integration across time. It is important to note that the hypotheses tests in (3.5), (3.6), and (3.7) are identical to tests for multivariate Granger causality or the maximum likelihood estimation of a

[142] Our method is similar to BDK but we apply the correct degrees of freedom (df). Instead of using

restricted VAR characterised by block exogeniety[143]. Geweke measures however have the advantage over standard Granger causality[144] tests because the asymptotic distribution of the measures of linear dependence and feedback is also known under the alternative hypothesis - that feedback is present. This was one of the motivations of the measures of feedback defined by Geweke. As Geweke (1982) stated:

> "....the maximum likelihood estimate of $F_{Y \to X}$ is simple to construct; and the
>
> asymptotic distribution of $F_{Y \to X}$ is the well know chi square under the null
>
> that $F_{Y \to X} = 0$, and may be approximated under the alternative."

See Geweke (1982) and the accompanying discussions by other eminent econometricians, for further details.

To test the hypotheses in (3.5), (3.6) and (3.7), we estimate the system in (3.1) and (3.2) by Seemingly Unrelated Regression (SUR)[145] estimation methods and estimate restricted equation (3.3) and (3.4) individually by Ordinary Least Squares (OLS). Enders (1996) noted that there are efficiency gains in using SUR methods to estimate a system such as those in (3.1) and (3.2) because we have a near-VAR system with different lag lengths on right hand variables. We also allow for contemporaneous correlation of the residuals. Standard OLS is more appropriate for equations (3.3) and (3.4) because estimating them as a system would yield no

---

1 df as done in the BDK paper, we use df = the number of restrictions. See Hamilton (1994b).

[143] See Hamilton (1994b) for details.

[144] The concept is due to Granger (1969) and it is causality in the sense that one series leads or lags another – this means that a lead-lag relationship exists between variables in a multivariate time series. Granger (1988) provides an excellent overview of these issues.

improvement in the efficiency of the estimates. These two sets of estimates are what we use to test the hypotheses in (3.5), (3.6) and (3.7) respectively.

3.2.2 Dynamic panel data (DPD) model

We use a DPD model in stage two of our analysis to assess the strength of the relationship (if any) between our calculated measures of integration and selected macroeconomic variables that influence bilateral trade relationships between the pair of countries. Because a DPD model has a lagged dependent variable, it allows us to study both the dynamic behaviour of integration between the markets and, the economic determinants of the levels of integration and feedback. This type of model gives us a better understanding of the time varying nature of integration and the interactions between financial integration and economic integration. Our DPD is based on estimators developed by Arellano and Bond (1991), Arellano and Bover (1995) and, Blundell and Bond (1998) as discussed by Doornik, et al. (2000) and applied by Beck, et al. (2000). The nature of these types of instrumental variables and generalised methods of moment (GMM)-type[146] estimators helps us address the problem of potential collinearity between the macroeconomic variables in our model particularly if Purchasing Power Parity (PPP) holds perfectly over time for the pairs of markets and, the possibility of correlation across the errors for different pairs of markets involving the same country, which could introduce a downward bias in the standard errors of the coefficients. These problems were also noted by BDK but not specifically addressed[147].

[145] This type of model was originally due to Arnold Zellner. See Judge and et al. (1988) for details.
[146] A general overview of the GMM estimator is provided in the appendix
[147] See note 17 p19 and note 19 p22 in Bracker, et al. (1999)

The DPD model used in this chapter comes from the general DPD model with individual effects. The general model takes the following form[148]:

$$y_{it} = \sum_{k=1}^{p} \alpha_k y_{i,t-k} + \beta'(L)x_{it} + \lambda_t + \eta_i + \upsilon_{it}, \ t = q+1,.....,T; \ i = 1,.....N \quad (3.8)$$

Where $y_{i,t-k}$ are lagged dependent variables – our measures of integration, x_{it} is a vector of explanatory variables (inflation differentials, interest rate differential and bilateral exchange rates) and $\beta'(L)$ are coefficients – polynomials in the lag operator.

η_i and λ_t are individual and time specific effects[149], q is the maximum lag length in the model and $\nu_{I,t}$ is an IID(0, σ^2_υ) error term. From the dynamic panel data literature we know that to fully identify this model, restrictions must be placed on the serial correlation properties of the error term and/or the explanatory variables. For example, if we assume that there is serial correlation in the error term, the model must to be transformed by placing restrictions on the parameters of the models. Although we assume that the errors are independently and identically distributed across individuals with mean zero[150], Doornik, et al. (2000) suggested that model could allow for some arbitrary form of heteroscedasticity.

Unfortunately, OLS estimation of a pooled regression with lagged dependent variable is inconsistent because the sample mean of $y_{i,t-k}$, the lagged dependent variable is correlated with that of the error term $\nu_{I,t}$. OLS estimation would generate

[148] The description of this model follows from Doornik, et al. (2000)
[149] These capture the effects of variables that are specific to a particular individual in the model in this case the 136 measures of bilateral levels of integration calculated.
[150] This is an example of a GMM orthogonality condition. See chapter 3 for more details.

biased estimates especially when the time dimension of the panel is small[151]. However, if there are valid instruments, instrumental variables or generalised methods of moments (GMM) estimation removes these inconsistencies. Using differenced variables as instruments for equations in levels is the main approach adopted in the literature. See Baltagi (2001) for details. This method of estimation also addresses the potential problem collinearity between explanatory variables because using the changes in the levels of these variables (differencing the variables) as instruments could remove the problem of collinearity. Our methodology therefore addresses some of the outstanding issues in the BDK paper and offers an improvement in estimation.

If we rewrite (3.8) in matrix form

$$y_i = W_i\delta + \iota_i\eta_i + \upsilon_i \quad (3.9)$$

Where δ is a parameter vector and W_i is a matrix containing the lagged dependent variables and the explanatory variables and time dummies and ι_i is a $(T_i - q)\times 1$ vector of ones. With the use of appropriate instrumental variables, Doornik, et al. (2000) computes various linear GMM estimators of δ with the general form as

$$\hat{\delta} = \left(\sum_i Z_i' W_i^*\right)^{-1}\left(\sum_i Z_i' y_i^*\right) \qquad (3.10)$$

[151] Kiviet (1995) and Judson and Owen (1999) discusses the various estimation methods for DPD models.

Where Z is a matrix of instrumental variables and, W_i^* and y_i^* are transformations of W_i and y_i - mainly levels, first differences, orthogonal deviations or combination of these[152].

In this chapter we estimate the following DPD model:

$$y_{it} = \alpha y_{i,t-1} + \beta'(L)x_{i,t} + \lambda_t + \eta_i + \upsilon_{i,t} \qquad (3.11)$$

All terms are as defined earlier. This was the best formulation from all the others we tried. The hypothesis in the model is that the lagged measures integration or feedback and the selected macroeconomic variable do not influence the levels of integration and feedback between the 136 pairs of markets we investigated. This can be written as follows:

H$_{1b}$: $\alpha = \beta'(L) = 0$

We test whether the scalar α and coefficient matrix $\beta'(L)$ in equation (3.11) are significant. In other words, does the level of the previous period's measure of integration and the selected macroeconomic variables affect the current level of contemporaneous integration and measures of unidirectional feedback or integration across days. This hypothesis addresses the issue of whether stock market integration is driven by economic convergence – an objective of this

[152] See chapter 3 of this thesis, Doornik, et al. (2000) and Baltagi (2001) For more details

chapter. The model also tests for the significance of individual and time specific effects using the appropriate orthogonality conditions (restrictions)[153].

We motivate this issue by observing the fact that with the increased globalisation of financial markets and the evolution in financial innovation we should expect a marked increase in capital mobility and some increase in asset substitutability particularly in the case of Europe where there is a common market. Given that there was also a concerted effort on the part of the European Union to achieve macroeconomic convergence before the implementation of the single currency, which happened in 1999 – the effects of which were ambitious targets for convergence in interest rates and inflation rates for the various countries wanting to join the single currency; examining the effects of macroeconomic convergence on capital integration will provide an invaluable insight into the interplay between financial markets and the wider macroeconomy. Like BDK, our hypothesis is to determine whether the deviations from Interest Rate Parity (IRP) and Purchasing Power Parity (PPP) are strongly associated with financial integration[154]. The nature of the relationship (the sign of the parameters) is crucial because deviations from IRP and PPP are likely to influence trade and capital flows between nations. An increase in the short-term real interest rate differential and inflation differential or increases in the bilateral exchange rate are expected to induce more capital movement and trade flows across days rather than on the same day. In other words deviations from IRP and PPP will only be useful in unlocking the lead/lag relationships between two counties. We also test the significance of the lagged

[153] The technical exposition of these is given in Baltagi (2001) pages 131 to 155. See also chapter 3 of this thesis for a concise exposition.
[154] See Chapter 2 for a brief review of IRP and PPP

dependent variable in this case our measures of contemporaneous integration or measures of unidirectional feedback or integration across days.

Our objective as stated above is to understand the dynamic behaviour of integration and, the interaction between the macroeconomy and the levels of integration that exist between the 17 European stock markets. We use both the one-step and two-step GMM estimators to estimate our model[155]. Data and preliminary econometric analysis are presented in next section.

3.2.3 Data

To implement the techniques discussed in the previous section, we use daily data of national stock price indices obtained from Datastream. The possible effects of non-synchronous trading in the markets and the potential effect on the analysis is acknowledged. However, since our study consists of only European capital markets where there is only a one-hour time difference between the UK and Ireland and the other European countries in the sample, should not be a serious problem. The Datastream Total Market Index calculated in local currency[156] was obtained for seventeen European stock markets (Table 3.1). The longest series runs from January 1978 to June 2001 and the shortest series from January 1992 – June 2001. Our choice of sample is due to the fact that we wanted the longest possible series that captures all the major events occurring in European capital markets during the 1980's and 1990's. The planning for the implementation of the euro took place in the 1980's and the early 1990's. The 1990's were also characterised by the onset of

[155] Although we tried other instrumental variables estimators, the one-step and two-step GMM produced the more robust estimates. See section 4.3

[156] Depending on the unique pairing of the markets, Total Market indices used are either denominated UK sterling, Euro synthetic or in local currency for the non-Euro countries. Datastream Advance 3.5 provides this functionality.

a recession in the UK, the UK's exit from the ERM in 1992, the international contagion effects of the financial crises in Russia and Asia and, the implementation of the euro. European economies would therefore be affected by these events.

Table 3.1

Market	Length of Series	Market	Length of Series
United Kingdom	1978 - 2001	Belgium	1978 - 2001
France	1978 - 2001	Switzerland	1978 - 2001
Germany	1978 - 2001	Austria	1978 - 2001
Denmark	1978 - 2001	Italy	1978 - 2001
Finland	1988 - 2001	Portugal	1990 - 2001
Norway	1980 - 2001	Rep. Of Ireland	1978 - 2001
Sweden	1982 - 2001	Greece	1988 - 2001
Netherlands	1978 - 2001	Spain	1988 - 2001
Luxemburg	1978 - 2001		

We were particularly interested in highlighting the effects – if any – of the following important dates[157]:

- 1978, the EMS is established based on the ECU
- 1979, the UK abolished exchange controls on the outward movement of capital from the UK which let to a monumental increase in the outward flow of portfolio investment from the UK[158]
- 1983, agreement on the 'new generation' Common Fisheries Policy
- 1986, The Single European Act
- 1990, UK joins the ERM; stage one of EMU begins
- 1992, Ratification of the Treaty of the EU (Maastricht); Britain leaves the ERM in September

[157] Most of this list is collated from the EUROPA web site listing of the history of the European Union: *http://europa.eu.int/abc/history/index_en.htm*

- 1993, establishment of the single market
- 1994, creation of the European Monetary Institute – the foundations of the ECB
- 1998, announcements of countries that satisfied the conditions for adoption of the euro on 1 January 1999
- 1999, the euro is officially launched on 1 January
- 2000, Denmark holds a referendum on the euro and the majority voted against joining the euro; final agreement on the Treaty of Nice
- 2001, the Treaty of Nice is signed. This amends the Treaty on the European Union and the Treaties establishing the European communities
- 2002, The euro coins and notes enter into circulation in the twelve participating Member States[159]

For all of the countries in our sample we cover all of these periods where data is available.

The Datastream calculated Total Market Index is generally regarded as the broadest index in each of these markets covering the most important stocks. In the UK for example the Datastream Total Market Index is equivalent to FTSE ALL Share Index. This methodology is replicated for all the 40 equity markets for which Datastream provides a Total Market Series.

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[158] See Taylor and Tonks (1989) for a general discussion on the liberalisation of the UK stock market in the 1980's.

[159] 2002 lies outside our sample period. The 12 participating member states are: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain.

We used local currency returns because we want study the concept of capital market integration from the point of view of a local investor wanting to invest abroad or is investing abroad.

For example when measuring integration between the UK and the other 16 European nations from the point of view of the UK investor, all the stock indices were converted in the UK Sterling. From the point of view of a French investor on the other hand, all the stock indices were converted into the Euro Synthetic indices. The Euro Synthetic conversion is a historic conversion of national currencies for countries in the Euro. From the stock price indices we calculated the continuously compounded stock returns series as the log price difference of the series. Using continuously compounded stock returns is standard practice in applied financial econometric research[160].

In stage two of our analysis we used three macroeconomic variables: the spread between the short-term real interest rates, the spread between the inflation rates and, the nominal bilateral exchange rates for the 136 pairs of countries in our sample. These variables are functions of the well-known standard Interest Rate Parity (IRP) and Purchasing Power Parity (PPP) conditions in international macroeconomics. It has been shown that deviations from uncovered interest parity (UIP) affects international stock returns. McCurdy and Morgan (1991) for example, showed that interest rate differentials have predictive power for the excess returns on the world equity index[161]. Employing these variables is consistent with the BDK paper. BDK used these variables to describe the economic

[160] See Campbell, et al. (1997) for more details.

conditions that influence bilateral trade relationships between nations. In addition to these, BDK constructed a bilateral trade statistics to measure the nature and extent of the bilateral trade relationship that exist between two countries. Due to the unavailability of sufficient bilateral trade data for our 136 pairs of European markets we have not used a direct measure of bilateral trade in our analysis. We will return to this issue again when we look at the results. Suffice it is to say at this stage that we believe that the levels of deviation from IRP and PPP on their own sufficiently explain the extent of capital and trade flows between any two countries.

We construct the real short-term interest rate differential, the inflation differential and cross nominal exchange rates between each unique pairing of markets. Short-term interest rate, inflation and European currency/US dollar exchange rates were obtained from the International Monetary Fund (IMF) international financial statistics dataset. Short-term interest rates were the benchmark Treasury bill rate given for each country. Inflation rates were calculated as the log difference of the consumer price index for each country. Cross nominal exchange rates were calculated from the European currency / dollar exchange for each pair of markets. The real exchange rate is the nominal exchange rate less the inflation rates[162]. Differentials are calculated as the difference between the rates of country 1 and those of country 2 in each of the 136 unique pairings. The pooled interest rate (Figure 3.1) and inflation differential (Figure 3.2) between the countries in the sample are depicted below. These variables seem to display significant variation over time.

[161] Other researchers such as Campbell (1987), Campbell (1990), Fama and French (1989) and Harvey (1991) have also found evidence in support of the predictive power of interest rates and interest rate spreads for international stock returns.

[162] As will be seen in the empirical results section we only report results with the nominal exchange rate instead of the real exchange rate. Models with nominal bilateral exchange rates were more robust than those with real bilateral exchange rates

Figure 3.1 Inflation differentials for panel data

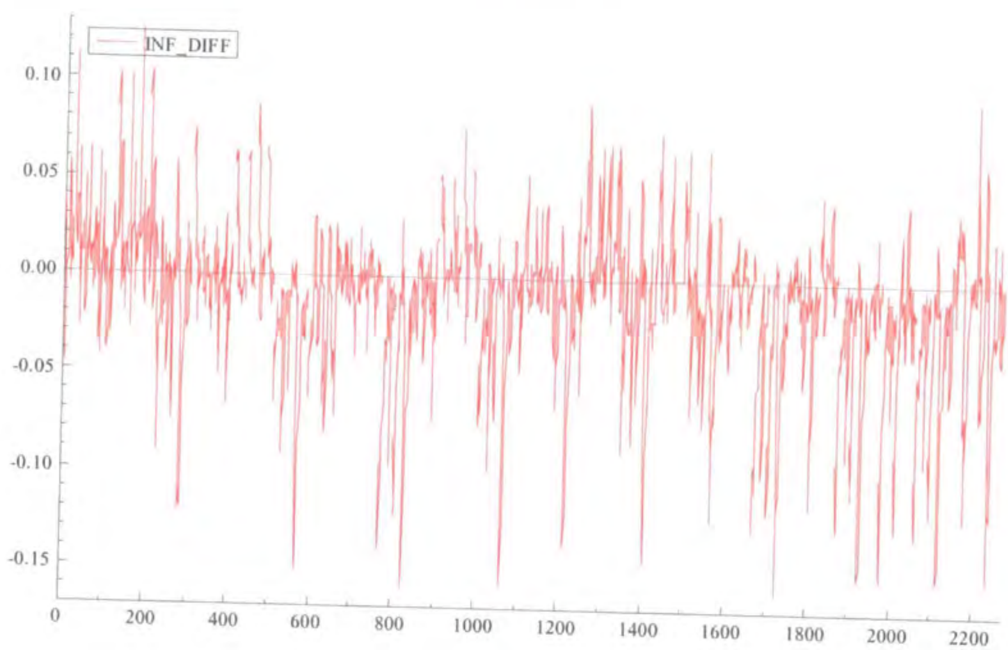
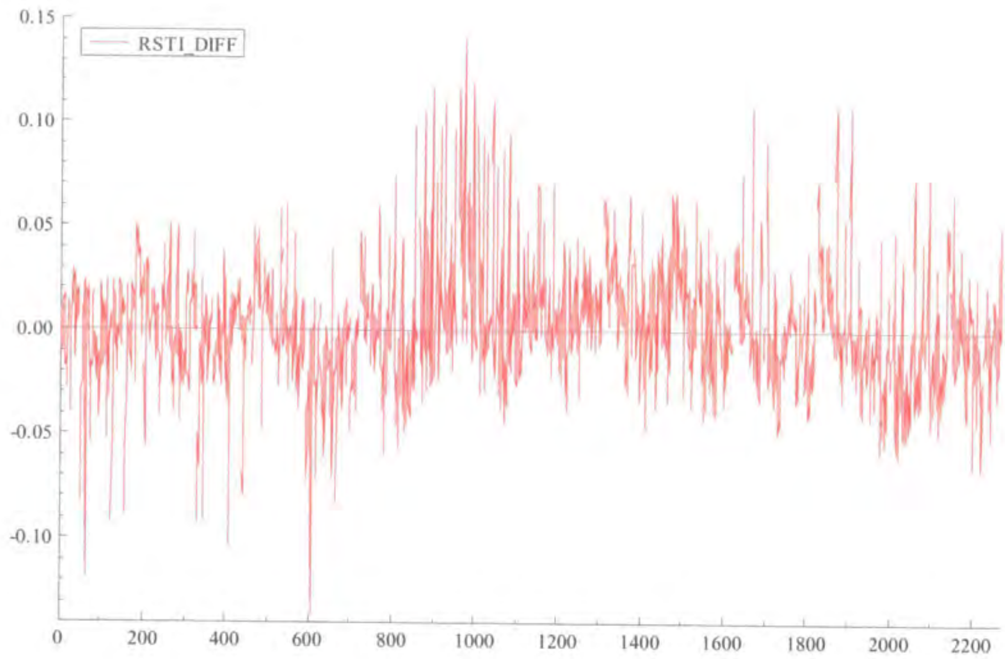


Figure 3.2 Real Interest rate differentials for Panel Data



The above graphs shows that the levels of real short-term interest rate and inflation differentials between all the pairs of markets in our sample vary considerably over time but also the differentials were significant towards the end of our sample although, overall, the differentials appear to have been falling.

3.2.4 Preliminary Econometric Analysis

As a preliminary econometric analysis we conducted unit roots tests for each of the price indices in our sample and cointegration tests[163] for each of the 136 pairs of markets in our sample. We found that all price indices were I(1) and none of the pairs of countries were cointegrated. This is not entirely surprising because stylised facts suggest that stock prices are nonstationary and very close to random walk and, returns are stationary. Our finding of no cointegration between any of the pairs of markets in our sample is consistent with the BDK study. The evidence on cointegration of stock price indices is mixed. Malliaris and Urrutia (1996) for

[163] Chapter 3 provides an overview of unit roots tests and cointegration analysis. In this chapter we use both the standard Dickey and Fuller (1979) test and the semi-parametric test proposed in Phillips (1987) and Phillips and Perron (1988)

example found that there was a valid error correction model for a selected pairing of European stock markets[164]. Malliaris and Urrutia (1996) used the top market indices in these markets instead of the broader indices that we used here or those used in the BDK paper[165]. In a multivariate context, Kasa (1992) and Masih and Masih (1997) found evidence of at least one significant cointegrating relationship between the countries in their sample[166]. This evidence on multivariate cointegration is also inconclusive. Masih and Masih (1997) for example found evidence of cointegration in the sub samples for periods before and after stock market crashes but found no evidence of cointegration over the entire sample in their analysis of "the dynamic linkages and the propagation mechanism driving international stock markets" before and after stock market crashes. Some evidence on cointegration between stock price indices was also provided by Abbott and Chow (1993) who employed the nonparametric canonical cointegrating regression methods.

We were also interested in discovering the potential effects of structural breaks and to see if these have masked in any way the true order of integration of each of the series. Due to Perron (1989), it is well known in the financial econometric time series literature that when a time series is generated by a process that is stationary about a broken trend or structural breaks, Dickey and Fuller (1979) unit root tests have very low power. Leybourne, et al. (1998) have also looked at the case where the true data generating process is integrated of the order one, but with a break and

[164] According to the Granger Representation Theorem it can be shown a valid error correction model implies cointegration

[165] As stated earlier we used the Datastream calculated indices for all the markets adjusted in local currency as required. The Datastream calculated index is the broadest index in each of these markets. For example in the case of the UK the Datastream calculated index is equivalent to the FTSE ALL SHARE index. BDK used the MSCI indices. MSCI indices are also broad indices which are larger than the indices used in the Malliaris and Urrutia (1996).

have shown that application of Dickey and Fuller (1979) can lead to a spurious rejection of the unit root null hypothesis. Hansen (2001) provides an excellent review of the literature on structural change and discusses the multitude of tests available to test for structural breaks in time series. For our purposes, we have employed the tests suggested by Perron (1989) and those suggested by Zivot and Andrews (1992) to test for structural breaks[167]. To implement Perron (1989) test, we imposed a pulse dummy where we suspect a break and apply standard Dickey and Fuller (1979) tests using appropriate Perron (1989) critical values. For the Zivot and Andrews (1992) tests, we did not assume any particular break point but allow the algorithm to search for any significant break point. Both tests revealed that all our series contained a unit root [I(1) series] although there was on average two significant break points. These results were not entirely surprising because they confirm what stylise facts suggests - stock prices mean revert and are very close to random walks. Campos, et al. (1996) and Gregory and Hansen (1996) have also suggested a method for testing for cointegration in the presence of structural breaks. Due to the fact that we have already discovered that all our price indices are I(1) from both standard unit root tests and unit root test in the presence of a structural change we did not apply the Campos, et al. (1996) methods here. We also believe that by implication, such tests would not have altered our initial findings that none of the 136 pairs of markets in our sample were cointegrated over the entire sample period.

Another very important preliminary econometric analysis in this study is to identify the correct parameterisation of our models in equations (3.1) to (3.4). We conduct

[166] The authors respectively applied the Johansen (1991) and Johansen and Juselius (1990) tests for multiple cointegrating vectors.

appropriate lag truncation tests using standard likelihood ratio statistics together with AIC and SBC information criterion[168]. These tests reveal that six lags of the dependent variables and three lags of other variable were the best near-VAR model for our data. This means that stock returns in each country is influence by six lags of its own past returns (six business days) and three lags of past returns in the other market (three business days).

The systems, equations and statistics in (3.1) – (3.7) were estimated on a 12-month annual rolling window in order to mimic the spectral decompositions described in Geweke (1982). The estimation task here is nontrivial. We have seventeen stock markets and we are pairing them two at a time. This gives 136 unique combinations and we therefore have to estimate 136 bilateral relationships. Given the length of the time series we have, we generated 2270 useable observations for each of the statistics in (3.5), (3.6), and (3.7)[169]. We also extracted variance decompositions and impulse response functions for each the systems estimated[170]. The generated measures of linear dependence (integration on the same day) and measures of unidirectional linear feedback (integration across days) were collated into annual time series observations for each of the 136 pairs of markets, which were used as dependent variables for our DPD models in stage two.

[167] Recently new methods for testing for multiple structural break and with supposedly stronger asymptotic theory have been suggested by Bai and Perron (1998) and Bai and Perron (2003).
[168] See Chapter 3 for details on these tests.
[169] With the exception of the combinations for UK, Germany, France and few other countries, I encountered problems in the estimation of the models in equations (4.1) to (4.4) when the data went beyond 31 December 2000. Because my code works well for some countries over the full sample I don't believe this was due to the functionality of my code. To resolve this issue, only results up to 31 December 2000 were used in the dynamic panel estimation although we have an unbalanced panel owing to the fact that we have different start dates for some of the price indices.

3.3 Empirical Results

3.3.1 Geweke measures of Linear Dependence and Feedback

For the analysis in stage one, 136 annual time series for the pairs of markets in our sample were generated. Depending on the length of the shorter series in every pairing, we have calculated a maximum of 24 annual Geweke measures for pairs of markets with stock return series for the entire dataset (1978 –2001) and a minimum of 10 annual Geweke measures for pairing involving Luxemburg which has the shortest useable series (1992 –2001) in our sample. For example when measuring integration between UK and Belgium we produce 24 annual measures of contemporaneous integration and unidirectional feedback because both countries have the full dataset (1978 - 2001). Due to space restrictions, stock market interdependence results are only reported for the UK, France and Germany[171]. Table 3.3.1a and 3.3.1b gives the 136 unique pairing used in our estimation.

Table 3.3.1a

UK	Fra	Ger	Den	Fin	Nor	Swe	Neth	Luxe
UK,Fra	Fra,Ger	Ger,Den	Den,Fin	Fin,Nor	Nor,Swe	Swe,Neth	Neth,Luxe	Luxe,Belg
UK,Ger	Fra,Den	Ger,Fin	Den,Nor	Fin,Swe	Nor,Neth	Swe,Luxe	Neth,Belg	Luxe,Swit
UK,Den	Fra,Fin	Ger,Nor	Den,Swe	Fin,Neth	Nor,Luxe	Swe,Belg	Neth,Swit	Luxe,Aust
UK,Fin	Fra,Nor	Ger,Swe	Den,Neth	Fin,Luxe	Nor,Belg	Swe,Swit	Neth,Aust	Luxe,Itat
UK,Nor	Fra,Swe	Ger,Neth	Den,Luxe	Fin,Belg	Nor,Swit	Swe,Aust	Neth,Itat	Luxe,Port
UK,Swe	Fra,Neth	Ger,Luxe	Den,Belg	Fin,Swit	Nor,Aust	Swe,Itat	Neth,Port	Luxe,Irel
UK,Neth	Fra,Luxe	Ger,Belg	Den,Swit	Fin,Aust	Nor,Itat	Swe,Port	Neth,Irel	Luxe,Gree
UK,Luxe	Fra,Belg	Ger,Swit	Den,Aust	Fin,Itat	Nor,Port	Swe,Irel	Neth,Gree	Luxe,Spai
UK,Belg	Fra,Swit	Ger,Aust	Den,Itat	Fin,Port	Nor,Irel	Swe,Gree	Neth,Spai	
UK,Swit	Fra,Aust	Ger,Itat	Den,Port	Fin,Irel	Nor,Gree	Swe,Spai		
UK,Aust	Fra,Itat	Ger,Port	Den,Irel	Fin,Gree	Nor,Spai			
UK,Itat	Fra,Port	Ger,Irel	Den,Gree	Fin,Spai				
UK,Port	Fra,Irel	Ger,Gree	Den,Spai					
UK,Irel	Fra,Gree	Ger,Spai						
UK,Gree	Fra,Spai							
UK,Spai								

[170] These were used as a first pass test to assess the nature and effects of impact multipliers in the bivariate relationship between the markets. The result generally supports the evidence of strong linear dependence between most of the markets on the same day.

[171] A full set all the results is available upon request.

Table 3.3.1b

Belg	Swit	Aust	Itat	Port	Irel	Gree	Spai
Belg,Swit	Swit,Aust	Aust,Itat	Itat,Port	Port,Irel	Irel,Gree	Gree,Spai	
Belg,Aust	Swit,Itat	Aust,Port	Itat,Irel	Port,Gree	Irel,Spai		
Belg,Itat	Swit,Port	Aust,Irel	Itat,Gree	Port,Spai			
Belg,Port	Swit,Irel	Aust,Gree	Itat,Spai				
Belg,Irel	Swit,Gree	Aust,Spai					
Belg,Gree	Swit,Spai						
Belg,Spai							

136 Combinations

The above tables are the unique pairing of the 17 markets used in our sample to estimate Geweke measures of linear dependence and feedback between multiple time series. The headings are the names of the countries/markets represented by the first three letters.

3.3.2 UK Results

Table 3.3.2 UK Results

Table 3.3.2ai and 3.3.2aii: Measuring Integration between UK and 16 European Countries on the same day - Geweke's Measure of Linear Dependence - distributed Chi Sq 9 degrees of freedom (df) - This is the measure of contemporaneous relationship on the same day

Table 3.3.2ai

	Germany			France			Denmark			Finland			Norway			Sweden		
Year	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig
1978	4.40	0.88		6.91	0.65		4.68	0.86										
1979	3.62	0.93		10.00	0.35		7.96	0.54										
1980	13.39	0.15		39.17	0.00	***	2.42	0.98					43.83	0.00	***			
1981	17.25	0.04	**	10.94	0.28		19.78	0.02	**				25.36	0.00	***			
1982	19.23	0.02	**	16.12	0.06	*	6.17	0.72					10.93	0.28		16.04	0.07	*
1983	17.27	0.04	**	23.05	0.01	***	6.12	0.73					28.85	0.00	***	4.39	0.88	
1984	24.44	0.00	***	22.04	0.01	***	18.09	0.03	**				41.90	0.00	***	22.67	0.01	***
1985	18.12	0.03	**	19.78	0.02	**	14.72	0.10	*				20.95	0.01	**	24.56	0.00	***
1986	9.81	0.37		5.25	0.81		6.62	0.68					14.87	0.09	*	13.68	0.13	
1987	80.41	0.00	***	106.25	0.00	***	76.72	0.00	***				185.85	0.00	***	93.03	0.00	***
1988	48.19	0.00	***	39.65	0.00	***	10.81	0.00	***	56.59	0.00	***	30.72	0.00	***	64.22	0.00	***
1989	21.49	0.01	**	36.41	0.00	***	4.59	0.03	**	4.41	0.04	**	33.20	0.00	***	13.95	0.00	***
1990	53.99	0.00	***	80.64	0.00	***	18.83	0.00	***	11.30	0.00	***	25.18	0.00	***	46.39	0.00	***
1991	93.56	0.00	***	170.09	0.00	***	47.93	0.00	***	12.56	0.00	***	82.73	0.00	***	40.67	0.00	***
1992	50.33	0.00	***	104.09	0.00	***	25.53	0.00	***	25.51	0.00	***	50.36	0.00	***	63.89	0.00	***
1993	28.16	0.00	***	82.01	0.00	***	14.71	0.00	***	8.41	0.00	***	21.42	0.00	***	41.38	0.00	***
1994	64.41	0.00	***	173.01	0.00	***	32.41	0.00	***	30.79	0.00	***	79.89	0.00	***	68.81	0.00	***
1995	32.13	0.00	***	84.54	0.00	***	21.49	0.00	***	28.84	0.00	***	37.09	0.00	***	80.65	0.00	***
1996	59.75	0.00	***	90.78	0.00	***	36.45	0.00	***	35.94	0.00	***	68.71	0.00	***	75.41	0.00	***
1997	132.76	0.00	***	155.99	0.00	***	93.90	0.00	***	170.82	0.00	***	93.02	0.00	***	187.85	0.00	***
1998	194.40	0.00	***	238.01	0.00	***	115.27	0.00	***	186.60	0.00	***	160.73	0.00	***	205.71	0.00	***
1999	120.30	0.00	***	146.46	0.00	***	26.26	0.00	***	94.28	0.00	***	58.87	0.00	***	85.98	0.00	***
2000	140.86	0.00	***	166.08	0.00	***	60.24	0.00	***	119.05	0.00	***	100.63	0.00	***	124.52	0.00	***
2001	102.45	0.00	***	126.20	0.00	***	32.01	0.00	***	59.77	0.00	***	81.96	0.00	***	86.55	0.00	***

*Estimated using equations (3.1)-(3.5); ***, **, and * denoting significance at 1%, 5% and 10%.*

The results in Tables 3.3.2ai - 3.3.2aiii are the calculated measures of linear dependence between UK and sixteen European countries from 1978 and 2001. The measures of linear dependence give the extent of stock market integration between the UK and the other countries on the same day. As these measures are chi squared distributed with 9 degrees of freedom representing the number of restrictions, the higher the measures the higher the levels of integration between the markets on the same day.

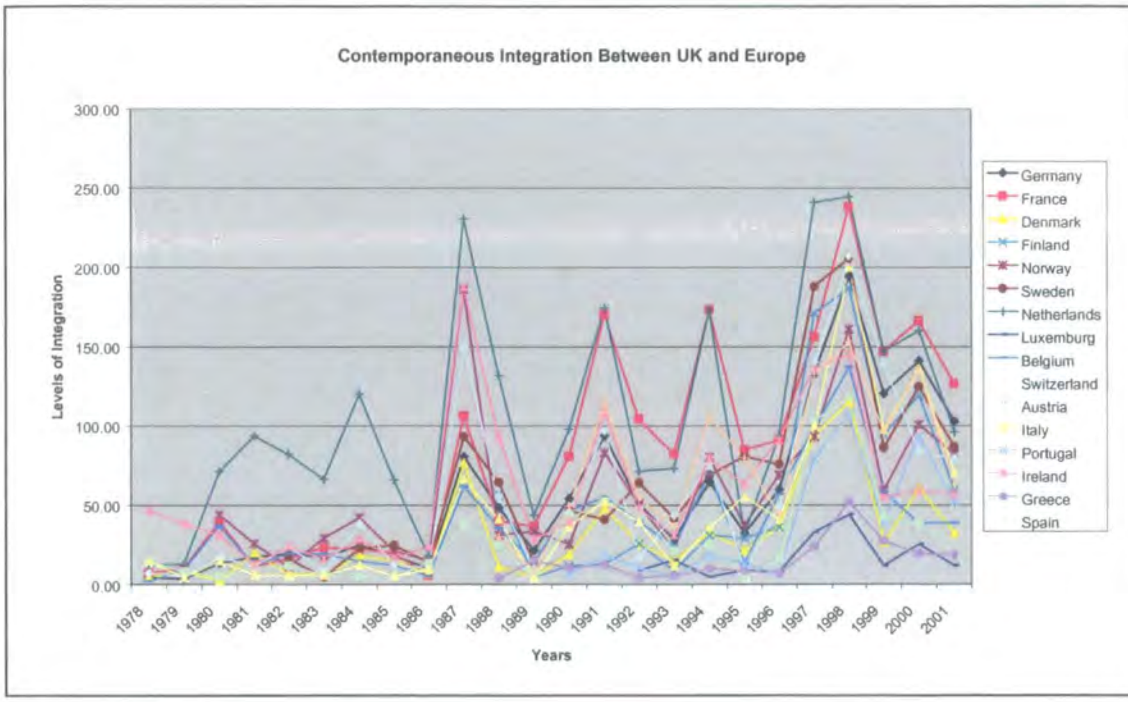
<u>Table 3.3.2aii and Table 3.3.2aiii:</u>

	Netherlands			Luxemburg			Belgium			Switzerland			Austria			Italy		
Year	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig
1978	12.18	0.20					1.93	0.99		6.81	0.66		14.36	0.11		14.44	0.11	
1979	12.71	0.18					9.17	0.42		5.65	0.77		8.02	0.53		4.29	0.89	
1980	70.88	0.00	***				36.69	0.00	***	17.31	0.04	**	5.20	0.82		14.74	0.10	*
1981	93.32	0.00	***				11.83	0.22		11.72	0.23		10.56	0.31		5.93	0.75	
1982	81.88	0.00	***				19.29	0.02	**	23.79	0.00	***	11.52	0.24		5.48	0.79	
1983	66.05	0.00	***				19.07	0.02	**	8.65	0.47		5.92	0.75		5.70	0.77	
1984	119.83	0.00	***				14.38	0.11		38.37	0.00	***	5.06	0.83		12.10	0.21	
1985	65.71	0.00	***				11.74	0.23		12.42	0.19		4.51	0.87		5.16	0.82	
1986	17.76	0.04	**				5.03	0.83		9.61	0.38		13.38	0.15		9.43	0.40	
1987	230.25	0.00	***				61.75	0.00	***	149.83	0.00	***	37.03	0.00	***	66.51	0.00	***
1988	131.56	0.00	***				35.42	0.00	***	55.51	0.00	***	24.79	0.00	***	40.88	0.00	***
1989	43.32	0.00	***				14.20	0.12		9.62	0.38		4.66	0.86		3.77	0.93	
1990	97.67	0.00	***				46.34	0.00	***	45.55	0.00	***	41.59	0.00	***	36.64	0.00	***
1991	174.27	0.00	***				54.82	0.00	***	96.73	0.00	***	52.01	0.00	***	52.35	0.00	***
1992	71.07	0.00	***	8.56	0.48		39.31	0.00	***	17.29	0.04	**	46.47	0.00	***	39.46	0.00	***
1993	73.00	0.00	***	15.15	0.09	*	23.74	0.00	***	43.21	0.00	***	21.24	0.01	**	11.25	0.26	
1994	172.57	0.00	***	4.53	0.87		69.49	0.00	***	76.29	0.00	***	24.93	0.00	***	36.24	0.00	***
1995	31.41	0.00	***	8.79	0.46		13.15	0.16		9.53	0.39		3.67	0.93		55.40	0.00	***
1996	93.62	0.00	***	7.50	0.58		56.79	0.00	***	49.27	0.00	***	16.76	0.05	*	41.07	0.00	***
1997	240.81	0.00	***	32.80	0.00	***	98.14	0.00	***	140.17	0.00	***	102.88	0.00	***	99.88	0.00	***
1998	244.39	0.00	***	43.94	0.00	***	136.84	0.00	***	207.20	0.00	***	118.51	0.00	***	199.73	0.00	***
1999	146.61	0.00	***	11.71	0.23		58.28	0.00	***	138.74	0.00	***	41.88	0.00	***	97.42	0.00	***
2000	159.73	0.00	***	25.14	0.00	***	38.31	0.00	***	83.49	0.00	***	38.36	0.00	***	136.04	0.00	***
2001	95.85	0.00	***	11.66	0.23		38.62	0.00	***	79.29	0.00	***	19.41	0.02	**	70.06	0.00	***

Year	Portugal Stats	Portugal P-Value	Portugal Sig	Ireland Stats	Ireland P-Value	Ireland Sig	Greece Stats	Greece P-Value	Greece Sig	Spain Stats	Spain P-Value	Spain Sig
1978				46.54	0.00	***						
1979				37.91	0.00	***						
1980				30.61	0.00	***						
1981				12.60	0.18							
1982				23.40	0.01	***						
1983				16.07	0.07	*						
1984				27.82	0.00	***						
1985				16.49	0.06	*						
1986				23.21	0.01	***						
1987				186.95	0.00	***						
1988				93.24	0.00	***	3.66	0.93		29.60	0.00	***
1989				28.03	0.00	***	14.73	0.10	*	8.61	0.47	
1990	6.26	0.71		39.14	0.00	***	10.11	0.34		49.30	0.00	***
1991	17.67	0.04	**	108.25	0.00	***	12.15	0.21		114.59	0.00	***
1992	10.33	0.32		47.94	0.00	***	3.76	0.93		53.99	0.00	***
1993	4.10	0.90		30.43	0.00	***	4.80	0.85		36.62	0.00	***
1994	18.03	0.03	**	79.07	0.00	***	9.70	0.38		105.86	0.00	***
1995	12.70	0.18		62.87	0.00	***	8.47	0.49		79.63	0.00	***
1996	6.68	0.67		90.69	0.00	***	6.79	0.66		43.46	0.00	***
1997	79.01	0.00	***	135.27	0.00	***	23.30	0.01	***	132.81	0.00	***
1998	107.34	0.00	***	145.22	0.00	***	51.90	0.00	***	153.06	0.00	***
1999	38.53	0.00	***	54.41	0.00	***	27.21	0.00	***	95.77	0.00	***
2000	92.97	0.00	***	58.64	0.00	***	19.14	0.02	**	135.08	0.00	***
2001	51.63	0.00	***	56.51	0.00	***	18.30	0.03	**	62.58	0.00	***

*Both tables estimated using (3.1) – (3.5). ***, ** and * denoting significance at 1%, 5% and 10%*

Figure 4.3.2a: Tables 3.3.2ai, 3.3.2.aii and 3.3.2aiii presented in graphical format



The above results reveal a very strong evidence of linear dependence or contemporaneous relationship between the UK and the other sixteen European stock markets. This strong evidence suggests that the 17 markets in our sample appear to be fully integrated during a 24-hour period and there is significant co-movement across all the markets. This can be seen from the large number of significant statistics in the tables and by the generally higher statistic report in the tables. Over 96% of the measures reported were either significant at the 5% or 1% level. The graph in figure 3.3.2a[172] also illustrates the strength of the relationship between the UK and the other markets. This strong evidence of linear dependence and integration on the same day supports the concept of international capital

[172] The 5% chi square (with 9 df) critical value is 16.9

market efficiency. Because that the markets are strongly interdependent on same day, by implication new information must be instantaneously impounded in the prices across the pairs of markets making the possibility of earning abnormal returns on the same day very slim.

Although this finding is consistent with the BDK paper, which uses a smaller dataset, our results reveal that the level of integration between some European stock markets with the UK stock market only intensified in the 1990's. Results from 1988 onwards are higher than those in earlier years and despite the swings, this increase is a sustained one. The evolving dynamics and time variation of the relationship between the London stock exchange and the other markets can be clearly seen by looking at the change in magnitude of our calculated measures of linear dependence between the UK and the other markets. This result was replicated for most of the other 136 pairing of markets we estimated for. The UK displays a greater co-movement with France and Germany than for any other market in the sample although the co-movement with France appears to be stronger than for those with Germany. This stronger interdependence between UK, France and Germany on the same day may be due to the fact that they are the largest and most advanced stock markets in Europe and have very strong trade links and, are generally regarded as the driving markets in Europe. It is also important to note that despite the strong evidence of contemporaneous integration overall, for some countries this has only happened recently: Luxemburg, Portugal and Greece only became integrated from 1997 although these markets have been in existence for at least five years.

<u>Table 3.3.2bi, 3.3.2bii and 3.3.2biii: Measuring Integration between UK and 16 European Countries across days - Geweke's Measure of unidirectional feedback</u>

from Europe to UK - distributed Chi Sq 3 df – This measures how Europe affects UK across days (H_2)

Table 3.3.2bi

	Germany			France			Denmark			Finland			Norway			Sweden		
Year	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig
1978	1.62	0.66		2.25	0.52		1.18	0.76										
1979	1.76	0.62		3.46	0.33		2.04	0.56										
1980	0.67	0.88		3.28	0.35		1.50	0.68					4.87	0.18				
1981	0.78	0.85		0.96	0.81		4.21	0.24					2.72	0.44				
1982	8.69	0.03	**	9.09	0.03	**	0.60	0.90					2.02	0.57		3.89	0.27	
1983	1.07	0.78		7.92	0.05	**	4.46	0.22					8.09	0.04	**	1.89	0.60	
1984	0.34	0.95		1.84	0.61		1.55	0.67					13.34	0.00	***	7.69	0.05	*
1985	1.99	0.57		1.58	0.66		10.63	0.01	**				1.25	0.74		12.51	0.01	***
1986	5.18	0.16		4.89	0.18		1.96	0.58					3.58	0.31		6.10	0.11	
1987	3.46	0.33		19.31	0.00	***	10.36	0.02	**				17.57	0.00	***	3.49	0.32	
1988	3.40	0.33		5.54	0.14		1.89	0.59		50.04	0.00	***	1.34	0.72		12.28	0.01	***
1989	0.25	0.97		1.96	0.58		1.32	0.72		2.30	0.51		1.50	0.68		0.18	0.98	
1990	2.79	0.43		5.09	0.17		1.00	0.80		3.83	0.28		2.49	0.48		6.65	0.08	*
1991	8.07	0.04	**	3.27	0.35		4.70	0.20		0.31	0.96		0.74	0.86		1.18	0.76	
1992	8.63	0.03	**	2.25	0.52		7.63	0.05	*	6.23	0.10		-0.17			8.46	0.04	**
1993	1.74	0.63		2.25	0.52		1.35	0.72		3.71	0.29		5.28	0.15		4.22	0.24	
1994	0.70	0.87		5.38	0.15		0.13	0.99		-0.02			1.30	0.73		0.24	0.97	
1995	1.71	0.63		1.25	0.74		7.03	0.07	*	7.71	0.05	*	1.33	0.72		0.01	1.00	
1996	12.31	0.01	***	2.04	0.56		5.56	0.14		5.85	0.12		4.28	0.23		1.01	0.80	
1997	1.79	0.62		0.66	0.88		1.33	0.72		11.32	0.01	**	0.04	1.00		-0.60		
1998	1.80	0.61		2.11	0.55		3.51	0.32		1.07	0.78		0.67	0.88		-3.27		
1999	1.32	0.72		2.73	0.44		5.76	0.12		1.38	0.71		4.07	0.25		3.26	0.35	
2000	1.19	0.76		1.36	0.71		0.32	0.96		1.39	0.71		3.39	0.33		5.33	0.15	
2001	3.34	0.34		2.61	0.46		-0.10			3.22	0.36		3.02	0.39		2.00	0.57	

*Estimated using equations (3.1)-(3.4) and (3.6); ***, **, and * denoting significance at 1%, 5% and 10%.*

The results in tables 3.3.2bi to 3.3.2biii and the graph in figure 3.3.2b gives the measures of unidirectional feedback between the UK and the other 16 European markets, with feedback emanating from Europe. They show how each of the sixteen European countries affects UK across days. From our model we hypothesise that three lags of returns in each European market affects the current levels of return in the UK. This means that the effect of European information in the UK market lasts for three days. In other words, the UK market lags the other European markets by three business days. The results show that this hypothesis is flatly rejected in almost all years and for all pairings. Of the 323 measures calculated here only 44 were significant at conventional levels. This represents about 14%. In terms of the number of significant statistics, the Republic of Ireland stock market appears to affect the UK stock market the most with 38% of the unidirectional feedback statistics calculated significant at conventional levels. The failure to reject H_2 for the UK bilateral relationships – with the overall lack of feedback from Europe to UK – suggests that the sixteen European markets do not lead the UK stock market.

Looking at Figure3.3.2b we see a better picture of this relationship with conventional chi squared critical values at 6.25, 7.81 and 11.34 for the 10%, 5% and 1% level of significance. Most of the statistics are bellow these levels. It however interesting to note the very high statistic reported for Finland in 1988. This was the first full trading year Finnish stock market. This was an emerging market in 1998 and must have been very attractive to UK investors. However we notice that the levels of unidirectional feedback from Finland to UK dropped significantly after this year. In fact, only 2 of the remaining 13 statistics were significant.

Table 3.3.2bii and Table 3.3.2biii

	Netherlands			Luxemburg			Belgium			Switzerland			Austria			Italy		
Year	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig
1978	6.59	0.09	*				0.60	0.90		2.31	0.51		3.18	0.37		12.00	0.01	***
1979	2.34	0.50					7.70	0.05	*	2.02	0.57		0.62	0.89		2.49	0.48	
1980	0.26	0.97					1.90	0.59		0.42	0.94		0.34	0.95		1.38	0.71	
1981	4.71	0.19					3.42	0.33		4.44	0.22		6.06	0.11		0.44	0.93	
1982	9.84	0.02	**				6.86	0.08	*	8.00	0.05	**	3.07	0.38		1.10	0.78	
1983	2.00	0.57					8.15	0.04	**	1.32	0.72		1.99	0.57		1.49	0.68	
1984	1.31	0.73					6.00	0.11		2.25	0.52		1.62	0.66		7.69	0.05	*
1985	0.96	0.81					2.19	0.53		0.66	0.88		2.86	0.41		0.20	0.98	
1986	0.34	0.95					1.47	0.69		2.38	0.50		3.68	0.30		2.11	0.55	
1987	-0.55						21.97	0.00	***	6.65	0.08	*	5.99	0.11		3.95	0.27	
1988	1.82	0.61					8.61	0.03	**	11.28	0.01	**	9.61	0.02	**	16.66	0.00	***
1989	-0.09						2.07	0.56		0.70	0.87		3.18	0.36		1.34	0.72	
1990	8.97	0.03	**				1.86	0.60		1.68	0.64		0.86	0.84		6.35	0.10	*
1991	3.15	0.37					-0.95			-0.49	0.98		2.69	0.44		4.98	0.17	
1992	3.74	0.29		1.49	0.68		2.48	0.48		0.96	0.81		12.65	0.01	***	1.99	0.57	
1993	6.70	0.08	*	8.39	0.04	**	2.11	0.55		6.78	0.08	*	5.92	0.12		1.13	0.77	
1994	-0.60			0.26	0.97		2.22	0.53		-0.16			0.29	0.96		0.56	0.91	
1995	0.02	1.00		0.76	0.86		3.26	0.35		0.50	0.92		1.46	0.69		2.80	0.42	
1996	0.11	0.99		3.06	0.38		2.72	0.44		8.73	0.03	**	4.29	0.23		0.78	0.85	
1997	0.98	0.81		1.12	0.77		0.40	0.94		2.68	0.44		0.37	0.95		2.93	0.40	
1998	1.33	0.72		3.91	0.27		1.89	0.60		5.85	0.12		-0.93			-0.37		
1999	-0.40			3.03	0.39		0.67	0.88		4.82	0.19		0.62	0.89		6.14	0.10	
2000	2.09	0.55		4.44	0.22		4.54	0.21		1.92	0.59		2.17	0.54		2.36	0.50	
2001	1.62	0.65		-0.50			7.61	0.05	*	2.62	0.45		3.67	0.30		1.72	0.63	

Year	Portugal Stats	Portugal P-Value	Portugal Sig	Ireland Stats	Ireland P-Value	Ireland Sig	Greece Stats	Greece P-Value	Greece Sig	Spain Stats	Spain P-Value	Spain Sig
1978				7.30	0.06	*						
1979				0.75	0.86							
1980				2.65	0.45							
1981				1.58	0.66							
1982				3.27	0.35							
1983				2.51	0.47							
1984				6.88	0.08	*						
1985				3.22	0.36							
1986				8.94	0.03	**						
1987				16.76	0.00	***						
1988				1.05	0.79		0.59	0.90		3.92	0.27	
1989				7.34	0.06	*	3.74	0.29		0.29	0.96	
1990	-0.25			4.40	0.22		0.51	0.92		1.66	0.65	
1991	1.16	0.76		0.52	0.91		1.30	0.73		2.11	0.55	
1992	8.18	0.04	**	6.83	0.08	*	1.45	0.69		2.39	0.50	
1993	1.82	0.61		3.33	0.34		2.15	0.54		0.31	0.96	
1994	4.52	0.21		3.99	0.26		5.58	0.13		7.29	0.06	*
1995	1.39	0.71		1.45	0.69		4.63	0.20		1.66	0.65	
1996	3.16	0.37		3.53	0.32		1.06	0.79		2.40	0.49	
1997	1.42	0.70		7.39	0.06	*	7.30	0.06	*	1.45	0.69	
1998	0.93	0.82		9.28	0.03	**	-0.04			0.77	0.86	
1999	0.55	0.91		0.60	0.90		7.15	0.07	*	2.28	0.52	
2000	0.98	0.81		6.59	0.09	*	0.34	0.95		3.74	0.29	
2001	1.11	0.78		5.32	0.15		0.11	0.99		4.54	0.21	

*Estimated using equations (3.1)-(3.4) and (3.6); ***, **, and * denoting significance at 1%, 5% and 10%.*

Figure 3.3.2b: Tables 3.3.2bi, 4.3.2bii and 3.3.2biii presented in graphical format

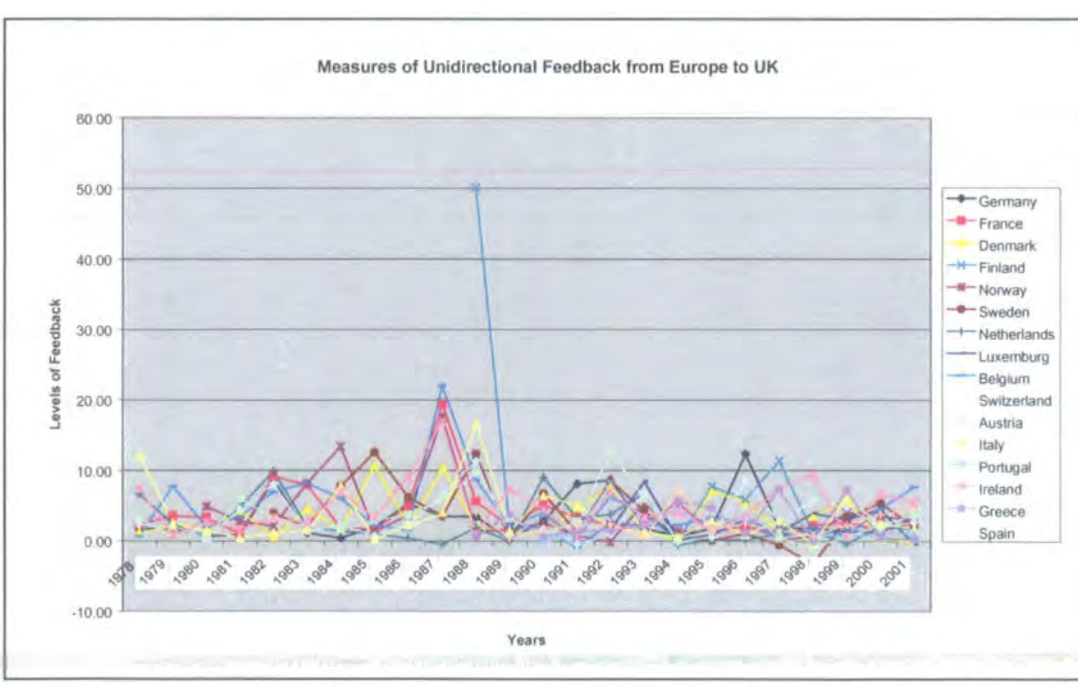


Table 3.3.2ci and 3.3.2cii: Measuring Integration between UK and 16 European Countries across days - Geweke's Measure of unidirectional feedback from UK to Europe - distributed Chi Sq 3 df – This measures how UK affects Europe across days (H_3)

Table 3.3.2ci

	Germany			France			Denmark			Finland			Norway			Sweden		
Year	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig
1978	0.40	0.94		3.93	0.27		0.63	0.89										
1979	1.28	0.73		1.99	0.57		3.32	0.34										
1980	0.17	0.98		1.07	0.79		0.91	0.82					16.11	0.00	***			
1981	3.75	0.29		5.00	0.17		7.95	0.05	**				12.56	0.01	***			
1982	4.23	0.24		1.74	0.63		5.14	0.16					5.30	0.15		10.66	0.01	**
1983	3.53	0.32		2.59	0.46		1.66	0.65					7.37	0.06	*	1.34	0.72	
1984	3.06	0.38		2.12	0.55		10.86	0.01	**				23.53	0.00	***	12.52	0.01	***
1985	2.78	0.43		3.97	0.26		1.44	0.70					1.89	0.60		8.78	0.03	**
1986	4.49	0.21		0.35	0.95		4.08	0.25					11.29	0.01	**	6.50	0.09	*
1987	4.83	0.18		7.26	0.06	*	14.45	0.00	***				15.63	0.00	***	4.64	0.20	
1988	27.83	0.00	***	3.85	0.28		5.90	0.12		6.51	0.09	*	7.78	0.05	*	12.30	0.01	***
1989	4.51	0.21		0.64	0.89		2.67	0.44		1.52	0.68		6.24	0.10		4.17	0.24	
1990	4.09	0.25		10.66	0.01	**	12.72	0.01	***	7.28	0.06	*	1.64	0.65		1.51	0.68	
1991	-0.11			-1.87			2.59	0.46		7.09	0.07	*	-0.24			2.80	0.42	
1992	9.57	0.02	**	-1.66			12.77	0.01	***	9.43	0.02	**	0.33	0.95		2.57	0.46	
1993	4.28	0.23		-0.48			8.22	0.04	**	3.46	0.33		1.37	0.71		5.59	0.13	
1994	14.67	0.00	***	2.97	0.40		8.87	0.03	**	10.61	0.01	**	2.86	0.41		3.77	0.29	
1995	12.75	0.01	***	-0.75			12.30	0.01	***	2.03	0.57		1.13	0.77		-0.07		
1996	5.38	0.15		3.48	0.32		9.01	0.03	**	1.57	0.67		0.20	0.98		8.43	0.04	**
1997	26.67	0.00	***	3.32	0.34		30.79	0.00	***	16.03	0.00	***	9.45	0.02	**	3.05	0.38	
1998	6.67	0.08	*	1.89	0.59		25.38	0.00	***	3.38	0.34		4.50	0.21		3.34	0.34	
1999	0.04	1.00		2.31	0.51		5.00	0.17		4.00	0.26		0.54	0.91		1.41	0.70	
2000	0.87	0.83		0.17	0.98		2.47	0.48		5.41	0.14		0.47	0.93		6.79	0.08	*
2001	0.47	0.93		1.29	0.73		5.58	0.13		5.61	0.13		10.44	0.02	**	3.45	0.33	

Table 3.3.2cii

Year	Netherlands			Luxemburg			Belgium			Switzerland			Austria			Italy		
	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig
1978	5.51	0.14					1.31	0.73		1.55	0.67		7.15	0.07	*	2.26	0.52	
1979	1.33	0.72					0.76	0.86		1.51	0.68		2.15	0.54		1.68	0.64	
1980	1.14	0.77					8.87	0.03	**	0.40	0.94		2.53	0.47		9.10	0.03	**
1981	3.18	0.36					1.06	0.79		0.28	0.96		4.36	0.23		5.08	0.17	
1982	8.30	0.04	**				7.56	0.06	*	7.58	0.06	*	7.39	0.06	*	4.27	0.23	
1983	2.88	0.41					10.90	0.01	**	3.81	0.28		3.94	0.27		1.48	0.69	
1984	1.38	0.71					8.11	0.04	**	15.50	0.00	***	1.51	0.68		2.86	0.41	
1985	4.24	0.24					5.93	0.12		4.39	0.22		1.09	0.78		4.63	0.20	
1986	3.15	0.37					3.54	0.32		6.86	0.08	*	3.36	0.34		6.01	0.11	
1987	1.20	0.75					4.29	0.23		12.40	0.01	***	30.35	0.00	***	12.63	0.01	***
1988	11.47	0.01	***				19.24	0.00	***	32.97	0.00	***	6.49	0.09	*	20.21	0.00	***
1989	0.04	1.00					12.07	0.01	***	4.50	0.21		1.33	0.72		2.41	0.49	
1990	3.83	0.28					10.86	0.01	**	2.66	0.45		7.49	0.06	*	10.77	0.01	**
1991	1.29	0.73					0.77	0.86		-1.11			2.65	0.45		4.45	0.22	
1992	-0.13			6.91	0.07	*	3.90	0.27		2.95	0.40		16.63	0.00	***	1.51	0.68	
1993	1.26	0.74		6.52	0.09	*	6.29	0.10	*	0.82	0.84		3.18	0.36		1.38	0.71	
1994	8.75	0.03	**	1.14	0.77		5.49	0.14		1.23	0.75		3.95	0.27		1.05	0.79	
1995	2.12	0.55		5.47	0.14		4.47	0.22		3.50	0.32		2.21	0.53		3.21	0.36	
1996	-0.58			3.73	0.29		6.23	0.10		0.75	0.86		1.36	0.71		3.29	0.35	
1997	2.70	0.44		24.25	0.00	***	7.06	0.07	*	3.68	0.30		19.13	0.00	***	3.01	0.39	
1998	7.12	0.07	*	24.26	0.00	***	10.43	0.02	**	3.56	0.31		5.91	0.12		3.83	0.28	
1999	0.12	0.99		7.96	0.05	**	0.26	0.97		0.42	0.94		5.20	0.16		0.76	0.86	
2000	3.75	0.29		0.25	0.97		11.73	0.01	***	3.70	0.30		4.50	0.21		2.50	0.48	
2001	-0.24			4.30	0.23		4.32	0.23		4.34	0.23		1.61	0.66		-0.31		

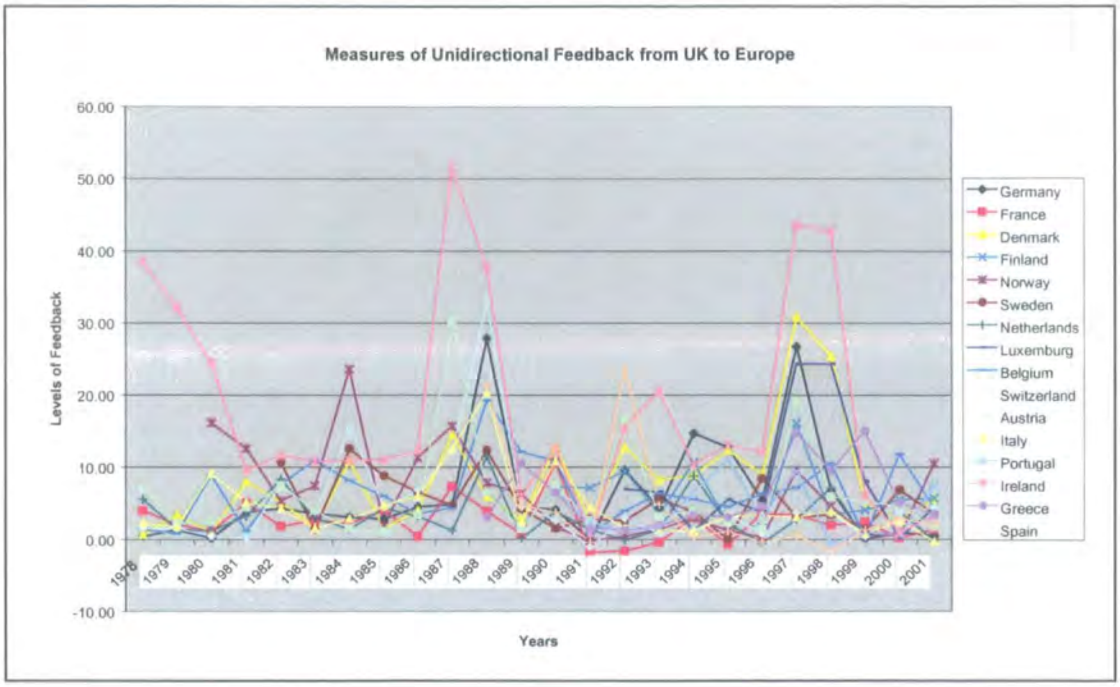
*Estimated using (3.1)-(3.4) and (3.7); where ***, **, and * denoting significance at 1%, 5% and 10%.*

Table 3.3.2ciii:

Year	Portugal			Ireland			Greece			Spain		
	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig
1978				38.39	0.00	***						
1979				32.10	0.00	***						
1980				24.39	0.00	***						
1981				9.54	0.02	**						
1982				11.56	0.01	***						
1983				10.73	0.01	**						
1984				10.91	0.01	**						
1985				11.00	0.01	**						
1986				12.31	0.01	***						
1987				51.52	0.00	***						
1988				37.71	0.00	***	3.06	0.38		21.31	0.00	***
1989				6.00	0.11		10.43	0.02	**	4.68	0.20	
1990	6.51	0.09	*	12.56	0.01	***	6.43	0.09	*	3.71	0.29	
1991	2.41	0.49		0.66	0.88		1.48	0.69		-0.42		
1992	1.08	0.78		15.36	0.00	***	1.24	0.74		23.69	0.00	***
1993	1.63	0.65		20.48	0.00	***	1.88	0.60		4.78	0.19	
1994	6.35	0.10	*	10.32	0.02	**	3.31	0.35		0.32	0.96	
1995	11.05	0.01	**	13.01	0.00	***	3.01	0.39		1.04	0.79	
1996	3.17	0.37		12.06	0.01	***	4.54	0.21		-0.42		
1997	9.35	0.02	**	43.47	0.00	***	14.71	0.00	***	0.54	0.91	
1998	-0.62			42.65	0.00	***	9.50	0.02	**	-1.68		
1999	1.00	0.80		5.95	0.11		14.94	0.00	***	1.30	0.73	
2000	0.56	0.90		0.91	0.82		4.92	0.18		2.80	0.42	
2001	7.34	0.06	*	3.12	0.37		3.40	0.33		1.99	0.58	

*Estimated using (3.1)-(3.4) and (3.7); ***, **, and * denoting significance at 1%, 5% and 10%*

Figure 3.3.2c: Tables 3.3.2ci, 3.3.2ciii and 3.3.2ciii presented in graphical format



The results in tables 3.3.2ci to 3.3.2ciii and the graph in figure 3.3.2c gives the measures of unidirectional feedback between the UK and the other 16 European markets, with feedback emanating from UK. These statistics show the extent to which the UK stock market affects the other European stock markets across days. Our hypothesis (**H_3**) here is that the UK stock market does not lead the other European markets across days. We are therefore assessing the impact of UK stock market information on other European stock markets over three business days.

The results suggest that UK stock market information affects other European stock markets more strongly than how the European markets affect the UK stock market. 101 of the 323 calculated measures were significant at conventional levels. This represents 31% of the measures of unidirectional feedback from UK to Europe.

Compared to the 14% for measures of unidirectional feedback from Europe to UK this is evidence that the UK stock market leads the European stock markets.

In terms of impact on individual countries the UK affects the Republic of Ireland stock market more than any other European market. 79% of the calculated measures of unidirectional feedback from the UK to the Republic of Ireland were significant at conventional levels. This was in contrast to the 25% of significant measures reported in the case of Germany although this is high in terms of the overall picture. The results for Germany indicate that between 1992 and 1998 the UK market more or less consistently led the German stock market. This point to some form of inefficiency in German stock market in terms of its bilateral relationship with the UK stock market between these periods. The UK's impact on the French stock market across days is the complete antithesis of its impact on Germany. Only in 1987 and 1990 did we reject $\mathbf{H}_3$ for France. The Paris bourse can be regarded as efficient in its bilateral relationship with the London stock exchange. The second most affected markets were Denmark and Belgium with 46% significant measures.

These results confirm that the UK stock markets leads the other markets across days which suggests, in general, the existence of some form of inefficiency in these other markets. Similar points were raised over a decade ago in a study by Taylor and Tonks (1989) who employed a Granger-causality test and were addressing a slightly different scenario to ours. Taylor and Tonks (1989) commented that their results:

> *... indicate the presence of Granger-causality running from the UK to the German, Dutch and Japanese markets, but not vice versa. For the US market, we found no strong*

evidence of cointegration with the UK market, there is no significant evidence of Granger-causality in either direction. These results confirm and clarify the implication of our cointegration results: since the British market appears to lead the German, Dutch and Japanese Markets this implies a subtle inefficiency in the latter markets. Except for the fact that London is probably the pre-eminent world financial centre, this finding, although interesting, is difficult to explain satisfactorily. We leave this on the agenda for future research...

Overall, all the results for the UK reported above suggests that the other sixteen European stock markets appear to lag the UK market more than the UK lags these markets. Although the results from Table 3.3.2ai/ii/iii reveal a strong evidence of market interdependence and co-movement on the same day, comparing the results from Table 3.3.2bi/ii/iii and those of 3.3.2ci/ii/iii we see that there are more significant statistics for unidirectional feedback from UK to Europe than there is from Europe to UK. This evidence confirms that the UK market is the leading financial market in Europe and the other European markets react more strongly to information emanating from the UK than vice versa.

We support the analogy that if there is a strong contemporaneous relationship on the same day but weaker evidence of feedback across days this is evidence of market efficiency and there exists very limited profitable opportunities beyond the 24-hour period. However, our results reveal a somewhat mixed picture since we have evidence of some lagged impact or feedback beyond the 24-hour period especially in the measures of unidirectional feedback from UK to Europe. These significant measures might suggests that an astute speculator or investor could benefit from profitable opportunities by taking long positions in those markets that exhibit significant feedback with the UK across days. However it must be noted that the level transactions costs that might be involved in such positions would significantly reduce the potential profits.

3.3.3 France Results

In this section we present results from our tests of capital market integration between France and fifteen European countries. From Table 3.3.1a we can see that France has 15 unique pairings or combinations. We study bilateral relationships in this way so as to avoid double counting. As previously, the measures of contemporaneous or same day integration are chi squared distributed with 9 degrees of freedom and, the measures of unidirectional feedback or lead/lag relationships are chi squared distributed with 3 degrees of freedom. The measures of integration are calculated from equations (3.1) to (3.5) and for the measures of unidirectional feedback from equations (3.1) to (3.4) and (3.6) and, equations (3.1) to (3.4) and (3.7) respectively. In this analysis France will be Market one and the other 15 European countries will be Market two individually.

Table 3.3.3 France Integration and Unidirectional Feedback Results

Table 3.3.3ai, 3.3.3aii and 3.3.3aiii: Measuring Integration between France and 16 European Countries on the same day - Geweke's Measure of Linear Dependence - distributed Chi Sq 9 df - This is the measure of contemporaneous relationship on the same day

Table 3.3.3ai

Year	Germany			Denmark			Finland			Norway			Sweden		
	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig
1978	12.51	0.19		9.49	0.39										
1979	16.06	0.07	*	1.73	1.00										
1980	42.06	0.00	***	5.62	0.78					53.89	0.00	***			
1981	12.41	0.19		20.90	0.01	**				18.55	0.03	**			
1982	37.00	0.00	***	18.94	0.03	**				28.58	0.00	***	13.26	0.15	
1983	42.24	0.00	***	14.57	0.10					29.77	0.00	***	15.33	0.08	*
1984	27.01	0.00	***	6.79	0.66					38.60	0.00	***	24.88	0.00	***
1985	20.59	0.01	**	10.18	0.34					16.79	0.05	*	23.60	0.00	***
1986	16.37	0.06	*	14.56	0.10					12.99	0.16		7.34	0.60	
1987	153.49	0.00	***	54.74	0.00	***				91.18	0.00	***	109.07	0.00	***
1988	61.62	0.00	***	22.13	0.01	***	90.73	0.00	***	29.59	0.00	***	57.20	0.00	***
1989	134.40	0.00	***	35.12	0.00	***	32.91	0.00	***	103.90	0.00	***	58.55	0.00	***
1990	194.32	0.00	***	45.65	0.00	***	6.65	0.67		49.60	0.00	***	100.58	0.00	***
1991	219.10	0.00	***	96.11	0.00	***	24.25	0.00	***	85.13	0.00	***	72.93	0.00	***
1992	121.85	0.00	***	33.85	0.00	***	37.45	0.00	***	71.45	0.00	***	89.36	0.00	***
1993	71.85	0.00	***	20.60	0.01	**	8.08	0.53		39.28	0.00	***	33.98	0.00	***
1994	123.05	0.00	***	39.34	0.00	***	35.01	0.00	***	74.08	0.00	***	85.48	0.00	***
1995	62.30	0.00	***	14.01	0.12		17.19	0.05	**	42.85	0.00	***	75.77	0.00	***
1996	108.52	0.00	***	72.30	0.00	***	53.74	0.00	***	78.14	0.00	***	107.83	0.00	***
1997	169.17	0.00	***	91.30	0.00	***	175.96	0.00	***	106.34	0.00	***	246.82	0.00	***
1998	281.11	0.00	***	130.64	0.00	***	242.76	0.00	***	163.29	0.00	***	271.80	0.00	***
1999	257.37	0.00	***	87.94	0.00	***	113.94	0.00	***	111.21	0.00	***	156.07	0.00	***
2000	317.31	0.00	***	60.80	0.00	***	158.17	0.00	***	110.56	0.00	***	181.45	0.00	***
2001	164.21	0.00	***	52.54	0.00	***	98.69	0.00	***	74.60	0.00	***	116.72	0.00	***

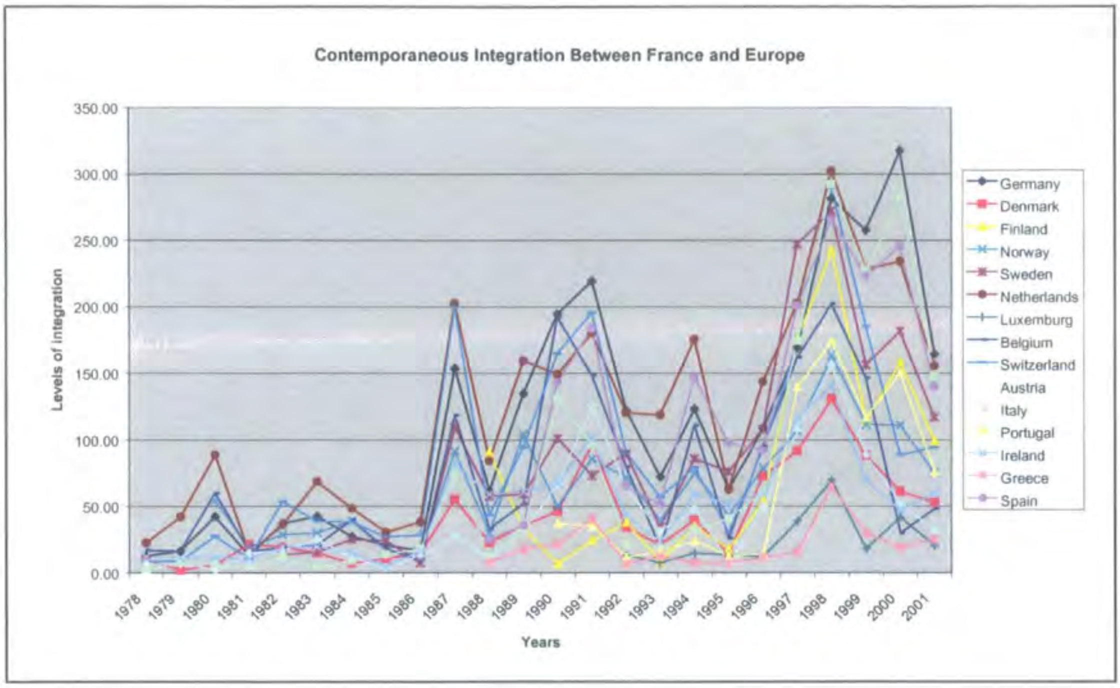
Table 3.3.3aii and Table 3.3.3aiii

	Netherlands			Luxemburg			Belgium			Switzerland			Austria		
Year	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig
1978	22.34	0.01	***				16.83	0.05	*	8.16	0.52		6.43	0.70	
1979	41.76	0.00	***				16.02	0.07	*	8.50	0.48		6.47	0.69	
1980	88.42	0.00	***				59.41	0.00	***	27.10	0.00	***	2.50	0.98	
1981	14.09	0.12					15.86	0.07	*	10.28	0.33		14.71	0.10	*
1982	36.01	0.00	***				18.38	0.03	**	53.17	0.00	***	16.78	0.05	*
1983	68.18	0.00	***				20.24	0.02	**	38.36	0.00	***	25.21	0.00	***
1984	48.20	0.00	***				39.77	0.00	***	37.69	0.00	***	11.34	0.25	
1985	30.21	0.00	***				17.28	0.04	**	26.71	0.00	***	3.63	0.93	
1986	37.98	0.00	***				9.15	0.42		28.00	0.00	***	13.16	0.16	
1987	202.12	0.00	***				118.26	0.00	***	199.53	0.00	***	27.71	0.00	***
1988	84.03	0.00	***				32.77	0.00	***	43.19	0.00	***	10.53	0.31	
1989	159.17	0.00	***				51.57	0.00	***	93.86	0.00	***	31.68	0.00	***
1990	149.02	0.00	***				192.07	0.00	***	164.46	0.00	***	66.94	0.00	***
1991	179.80	0.00	***				148.03	0.00	***	195.14	0.00	***	125.76	0.00	***
1992	119.96	0.00	***	12.73	0.18		79.12	0.00	***	89.85	0.00	***	63.45	0.00	***
1993	118.36	0.00	***	7.22	0.61		18.27	0.03	**	56.65	0.00	***	30.99	0.00	***
1994	175.19	0.00	***	14.40	0.11		110.88	0.00	***	78.83	0.00	***	47.96	0.00	***
1995	62.80	0.00	***	12.91	0.17		25.65	0.00	***	30.01	0.00	***	7.19	0.62	
1996	143.52	0.00	***	11.83	0.22		95.08	0.00	***	93.55	0.00	***	50.08	0.00	***
1997	202.37	0.00	***	38.45	0.00	***	161.71	0.00	***	172.68	0.00	***	107.99	0.00	***
1998	301.90	0.00	***	69.51	0.00	***	202.14	0.00	***	288.93	0.00	***	156.40	0.00	***
1999	228.07	0.00	***	17.74	0.04	**	146.06	0.00	***	184.65	0.00	***	88.45	0.00	***
2000	234.24	0.00	***	41.51	0.00	***	29.29	0.00	***	88.28	0.00	***	52.23	0.00	***
2001	155.38	0.00	***	19.99	0.02	**	47.81	0.00	***	94.19	0.00	***	31.82	0.00	***

	Italy			Portugal			Ireland			Greece			Spain		
Year	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig
1978	2.29	0.99					11.89	0.22							
1979	7.44	0.59					10.88	0.28							
1980	6.29	0.71					10.97	0.28							
1981	5.39	0.80					9.84	0.36							
1982	11.59	0.24					19.27	0.02	**						
1983	4.81	0.85					19.07	0.02	**						
1984	8.95	0.44					14.64	0.10							
1985	13.42	0.14					3.81	0.92							
1986	18.00	0.04	**				15.84	0.07	*						
1987	74.54	0.00	***				81.64	0.00	***						
1988	12.72	0.18					58.78	0.00	***	7.44	0.59		24.14	0.00	***
1989	36.29	0.00	***				60.42	0.00	***	17.42	0.04	**	35.37	0.00	***
1990	130.43	0.00	***	37.22	0.00	***	66.94	0.00	***	21.23	0.01	**	143.20	0.00	***
1991	95.95	0.00	***	35.24	0.00	***	101.09	0.00	***	39.76	0.00	***	183.33	0.00	***
1992	20.89	0.01	**	11.41	0.25		42.81	0.00	***	6.31	0.71		64.33	0.00	***
1993	18.59	0.03	**	16.09	0.07	*	22.91	0.01	***	12.22	0.20		51.05	0.00	***
1994	32.22	0.00	***	23.83	0.00	***	58.44	0.00	***	7.09	0.63		146.58	0.00	***
1995	40.47	0.00	***	12.14	0.21		51.47	0.00	***	6.65	0.67		97.26	0.00	***
1996	60.46	0.00	***	14.33	0.11		59.56	0.00	***	11.07	0.27		91.82	0.00	***
1997	174.22	0.00	***	139.59	0.00	***	116.90	0.00	***	15.12	0.09	*	200.66	0.00	***
1998	292.01	0.00	***	174.25	0.00	***	139.96	0.00	***	64.68	0.00	***	265.97	0.00	***
1999	227.44	0.00	***	116.45	0.00	***	68.73	0.00	***	29.32	0.00	***	222.84	0.00	***
2000	282.86	0.00	***	150.70	0.00	***	46.69	0.00	***	18.55	0.03	**	245.25	0.00	***
2001	147.38	0.00	***	75.40	0.00	***	59.29	0.00	***	24.68	0.00	***	140.06	0.00	***

*Tables 3.3.3ai/aii/aiii were estimated using equations (3.1) – (3.5) with France being country 1 and the other 15 European countries individually country 2. ***, ** and * denoting significance at 1%, 5% and 10%.*

Graph 3.3.3a: Tables 3.3.3ai, 3.3.3aii and 3.3.3aiii presented in graphical format



The results in Table 3.3.3ai/ii/iii and the graph in Figure 3.3.3a reveal the levels of contemporaneous or same day integration between France and fifteen European countries. The results show high levels of contemporaneous integration across the board. France appears to be fully integrated with the other fifteen European countries. This can be seen from the large number of significant statistics reported for $\mathbf{H}_1$ with over 80% of them significant at conventional levels. Like the UK, France became more integrated with the other countries towards the end of the 1980's and the beginning of the 1990's. France shows some evidence of integration with Portugal and Greece before 1997 unlike the case of the UK although, but like the UK, France only became integrated with Luxemburg from 1997 onwards. It is also interesting to note that France was strongly contemporaneously integrated with Spain over the entire sample period for which bilateral integration was measured. Overall the results support the notion of international capital market efficiency – on the same day – because there is strong interdependence on the same day, which suggests that information is almost instantaneously transmitted to all the markets.

Tables 3.3.3bi, 3.3.3bii and 3.3.3biii: Measuring Integration between France and 15 European Countries across days - Geweke's Measure of unidirectional feedback from Europe to France distributed Chi Sq 3 df – This measures how Europe affects France across days

Table 3.3.3bi

	Germany			Denmark			Finland			Norway			Sweden		
Year	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig
1978	4.65	0.20		1.99	0.57										
1979	0.39	0.94		0.42	0.94										
1980	14.96	0.00	***	3.14	0.37					1.22	0.75				
1981	5.18	0.16		3.58	0.31					2.73	0.43				
1982	4.09	0.25		0.15	0.98					-0.22			10.38	0.02	**
1983	-0.05			1.54	0.67					2.33	0.51		4.40	0.22	
1984	3.65	0.30		2.40	0.49					5.22	0.16		1.68	0.64	
1985	4.48	0.21		6.99	0.07	*				1.05	0.79		2.36	0.50	
1986	-0.11			4.97	0.17					5.55	0.14		0.73	0.87	
1987	2.51	0.47		2.28	0.52					0.54	0.91		1.98	0.58	
1988	0.15	0.98		9.56	0.02	**	75.31	0.00	***	2.68	0.44		5.09	0.17	
1989	9.26	0.03	**	2.29	0.51		7.78	0.05	*	7.83	0.05	**	13.57	0.00	***
1990	1.20	0.75		3.36	0.34		0.80	0.85		8.85	0.03	**	6.83	0.08	*
1991	9.54	0.02	**	5.34	0.15		3.49	0.32		2.91	0.41		0.68	0.88	
1992	2.14	0.54		6.02	0.11		3.54	0.32		1.98	0.58		3.74	0.29	
1993	3.12	0.37		11.61	0.01	***	1.95	0.58		3.51	0.32		6.09	0.11	
1994	3.19	0.36		2.10	0.55		0.84	0.84		0.15	0.99		4.52	0.21	
1995	10.54	0.01	**	0.66	0.88		3.82	0.28		1.79	0.62		6.93	0.07	*
1996	11.03	0.01	**	2.39	0.50		4.01	0.26		1.31	0.73		3.93	0.27	
1997	8.23	0.04	**	13.20	0.00	***	7.35	0.06	*	4.63	0.20		0.16	0.98	
1998	10.09	0.02	**	5.95	0.11		2.26	0.52		-0.95			-2.63		
1999	1.95	0.58		9.25	0.03	**	0.87	0.83		5.47	0.14		4.26	0.24	
2000	1.97	0.58		2.52	0.47		0.11	0.99		6.33	0.10	*	1.18	0.76	
2001	1.65	0.65		-0.02	0.98		2.05	0.56		4.12	0.25		0.74	0.86	

Table 3.3.3bi to 3.3.3biii and Figure 3.3.3b give the results for tests of $\mathbf{H_2}$ for France. We are testing whether the fifteen European markets leads the Paris bourse across days. The results suggest failure to reject $\mathbf{H_2}$ in most of the cases. Only 58 out of the 299 calculated measures were significant at conventional levels. This represents 19% of these measures, which is an increase of 5% over those reported for the UK. This is evidence that daily events in European stock markets impact the

Paris bourse more than they impact the London stock exchange. This means that to some extent more markets lead Paris across days and the UK market is probably more efficient than the French stock market. This has implications for the potential of earning abnormal profits.

Table 3.3.3bii

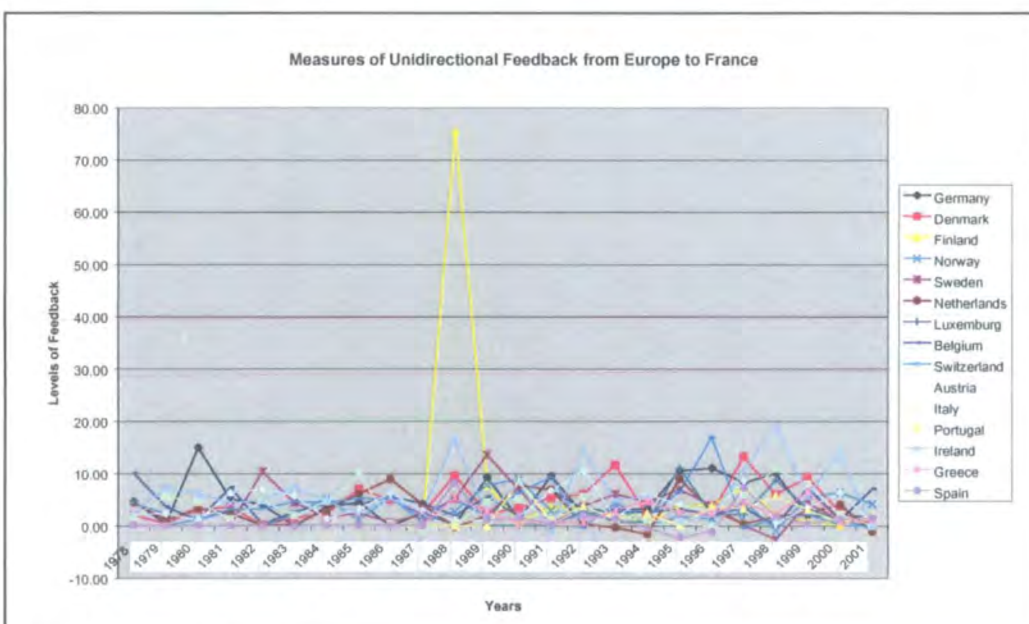
	Netherlands			Luxemburg			Belgium			Switzerland			Austria		
Year	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig
1978	4.47	0.22					10.06	0.02	**	4.42	0.22		2.17	0.54	
1979	1.15	0.76					3.64	0.30		2.21	0.53		2.35	0.50	
1980	3.32	0.34					1.05	0.79		1.29	0.73		1.21	0.75	
1981	2.35	0.50					7.30	0.06	*	3.06	0.38		6.26	0.10	*
1982	0.17	0.98					0.35	0.95		3.26	0.35		7.13	0.07	*
1983	0.18	0.98					2.67	0.44		4.57	0.21		5.76	0.12	
1984	3.13	0.37					4.23	0.24		4.50	0.21		1.36	0.72	
1985	6.18	0.10					4.09	0.25		5.22	0.16		3.28	0.35	
1986	8.91	0.03	**				5.54	0.14		5.19	0.16		6.20	0.10	
1987	4.06	0.26					4.24	0.24		1.68	0.64		2.93	0.40	
1988	-0.26						1.91	0.59		5.01	0.17		1.10	0.78	
1989	1.98	0.58					5.51	0.14		1.77	0.62		1.08	0.78	
1990	7.71	0.05	*				1.78	0.62		6.33	0.10	*	1.73	0.63	
1991	6.93	0.07	*				6.72	0.08	*	9.23	0.03	**	6.73	0.08	*
1992	0.35	0.95		2.79	0.42		3.33	0.34		-0.29			10.62	0.01	**
1993	-0.30			0.82	0.85		2.60	0.46		4.29	0.23		1.50	0.68	
1994	-1.58			0.69	0.88		2.62	0.45		1.68	0.64		6.05	0.11	
1995	8.92	0.03	**	11.00	0.01	**	3.18	0.36		6.53	0.09	*	4.14	0.25	
1996	2.86	0.41		2.13	0.55		2.17	0.54		16.91	0.00	***	2.44	0.49	
1997	0.37	0.95		2.17	0.54		3.38	0.34		-0.25			8.58	0.04	**
1998	1.79	0.62		8.77	0.03	**	-0.01			1.25	0.74		0.55	0.91	
1999	2.45	0.49		3.25	0.35		7.31	0.06	*	2.16	0.54		3.54	0.32	
2000	3.99	0.26		1.14	0.77		1.05	0.79		0.11	0.99		6.37	0.10	*
2001	-1.09			-0.34			7.00	0.07	*	-0.23			0.51	0.92	

Table 3.3.3biii

Year	Italy Stats	Italy P-Value	Italy Sig	Portugal Stats	Portugal P-Value	Portugal Sig	Ireland Stats	Ireland P-Value	Ireland Sig	Greece Stats	Greece P-Value	Greece Sig	Spain Stats	Spain P-Value	Spain Sig
1978	1.74	0.63					2.60	0.46							
1979	5.69	0.13					7.12	0.07	*						
1980	4.46	0.22					6.08	0.11							
1981	1.31	0.73					4.41	0.22							
1982	4.85	0.18					4.81	0.19							
1983	1.96	0.58					7.35	0.06	*						
1984	4.67	0.20					4.73	0.19							
1985	10.04	0.02	**				2.13	0.55							
1986	0.42	0.94					5.31	0.15							
1987	-0.79						2.45	0.48							
1988	0.49	0.92					16.20	0.00	***	5.34	0.15		8.25	0.04	**
1989	4.53	0.21					2.49	0.48		2.78	0.43		1.07	0.78	
1990	5.14	0.16		8.48	0.04	**	8.10	0.04	**	0.39	0.94		1.50	0.68	
1991	1.19	0.76		1.02	0.80		-0.94			0.37	0.95		0.37	0.95	
1992	5.56	0.14		3.72	0.29		14.43	0.00	***	0.66	0.88		1.93	0.59	
1993	1.71	0.63		1.43	0.70		4.93	0.18		2.94	0.40		1.39	0.71	
1994	1.18	0.76		2.40	0.49		5.55	0.14		4.64	0.20		-0.43		
1995	0.76	0.86		0.22	0.97		0.81	0.85		2.50	0.48		-2.32		
1996	-0.12			3.73	0.29		2.22	0.53		2.41	0.49		-1.11		
1997	5.95	0.11		3.28	0.35		10.58	0.01	**	4.43	0.22		7.19	0.07	*
1998	10.93	0.01	**	5.83	0.12		19.03	0.00	***	1.97	0.58		1.87	0.60	
1999	7.94	0.05	**	3.03	0.39		5.59	0.13		6.59	0.09	*	0.38	0.94	
2000	2.19	0.53		0.66	0.88		13.82	0.00	***	0.56	0.91		1.19	0.76	
2001	-0.01			1.98	0.58		-0.08			1.13	0.77		1.42	0.70	

*Tables 3.3.3bi – 3.3.3biii were estimated using equations (3.1) – (3.4) and (3.6) with France being country 1 and the other 15 European countries individually country 2; ***, ** and * denoting significance at 1%, 5% and 10%.*

Figure 3.3.3b: Tables 3.3.3bi, 3.3.3bii and 3.3.3bii presented in graphical format



Despite these modest increases, the failure to rejects $\mathbf{H_2}$ for France is indicative of the leading role – in terms of information flow – that the Paris bourse has over the other 15 European markets. Of all the markets studied, Germany and the Republic of Ireland lead the French market the most; based on the number of reported significant measures at conventional levels. The behaviour of the Finnish stock market in its maiden year in terms of how it affects the French stock market is similar to its behaviour to the UK. Looking at Figure 3.3.3b we see a huge spike for Finland in 1988 followed by big a fall in the level of significance in 1989. This is perhaps due to the fact that the Finnish market opened in 1988 and was very attractive and international investors seem to have descended on it 'en masse'.

In Table 3.3.3ci to 3.3.3ciii and Figure 3.3.3c below we give the results for the test (**H_3**) of the strength of unidirectional feedback from France to the other 15 European countries. We test whether the French stock market leads the other 15 European countries across days. The results suggest a general failure to reject **H_3**. There is however, reasonable evidence that some of the other 15 European markets display substantial information inefficiencies when compared with France. 118 out of the 299 calculated measures of unidirectional feedback from France to the other countries were significant at conventional levels. This is equivalent to 39% of our calculated measures. Compared to the results obtained for UK, for the same statistic, there is an increase of an additional 8% for the reported significant measures. This is evidence that the French stock market leads more markets across days in percentage terms than the UK does.

Tables 3.3.3ci, 3.3.3cii and 3.3.3ciii: Measuring Integration between France and 15 European Countries across days - Geweke's Measure of unidirectional feedback from France to Europe - distributed Chi Sq 3 df – This measures how France affects Europe across days

Table 3.3.3ci

Year	Germany			Denmark			Finland			Norway			Sweden		
	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig
1978	7.75	0.05	*	1.37	0.71										
1979	10.42	0.02	**	1.13	0.77										
1980	0.93	0.82		1.18	0.76					12.51	0.01	***			
1981	4.94	0.18		6.52	0.09	*				9.30	0.03	**			
1982	1.46	0.69		3.14	0.37					5.25	0.15		2.85	0.42	
1983	14.19	0.00	***	6.31	0.10	*				3.49	0.32		1.49	0.68	
1984	2.34	0.50		0.36	0.95					9.16	0.03	**	0.14	0.99	
1985	7.04	0.07	*	2.89	0.41					1.72	0.63		0.34	0.95	
1986	3.77	0.29		4.57	0.21					5.58	0.13		2.13	0.55	
1987	6.43	0.09	*	27.41	0.00	***				27.94	0.00	***	18.11	0.00	***
1988	14.20	0.00	***	7.81	0.05	*	15.19	0.00	***	6.20	0.10		15.47	0.00	***
1989	-0.89			0.68	0.88		11.44	0.01	***	2.02	0.57		1.95	0.58	
1990	2.71	0.44		11.69	0.01	***	5.79	0.12		1.73	0.63		4.22	0.24	
1991	0.02	1.00		0.11	0.99		12.28	0.01	***	3.08	0.38		1.40	0.70	
1992	7.51	0.06	*	15.16	0.00	***	17.10	0.00	***	0.17	0.98		4.25	0.24	
1993	16.04	0.00	***	8.04	0.05	**	3.84	0.28		0.92	0.82		6.17	0.10	
1994	30.83	0.00	***	8.95	0.03	**	13.08	0.00	***	2.37	0.50		6.61	0.09	*
1995	8.83	0.03	**	3.95	0.27		0.38	0.94		2.68	0.44		2.81	0.42	
1996	19.83	0.00	***	13.78	0.00	***	3.45	0.33		4.20	0.24		4.53	0.21	
1997	16.77	0.00	***	10.87	0.01	**	3.49	0.32		-0.20			-0.81		
1998	20.28	0.00	***	21.93	0.00	***	-1.93			2.94	0.40		2.34	0.51	
1999	11.39	0.01	***	17.47	0.00	***	1.50	0.68		5.46	0.14		5.42	0.14	
2000	2.56	0.47		6.67	0.08	*	5.47	0.14		0.48	0.92		1.35	0.72	
2001	-0.28			12.12	0.01	***	7.38	0.06	*	8.59	0.04	**	5.69	0.13	

Table 3.3.3cii

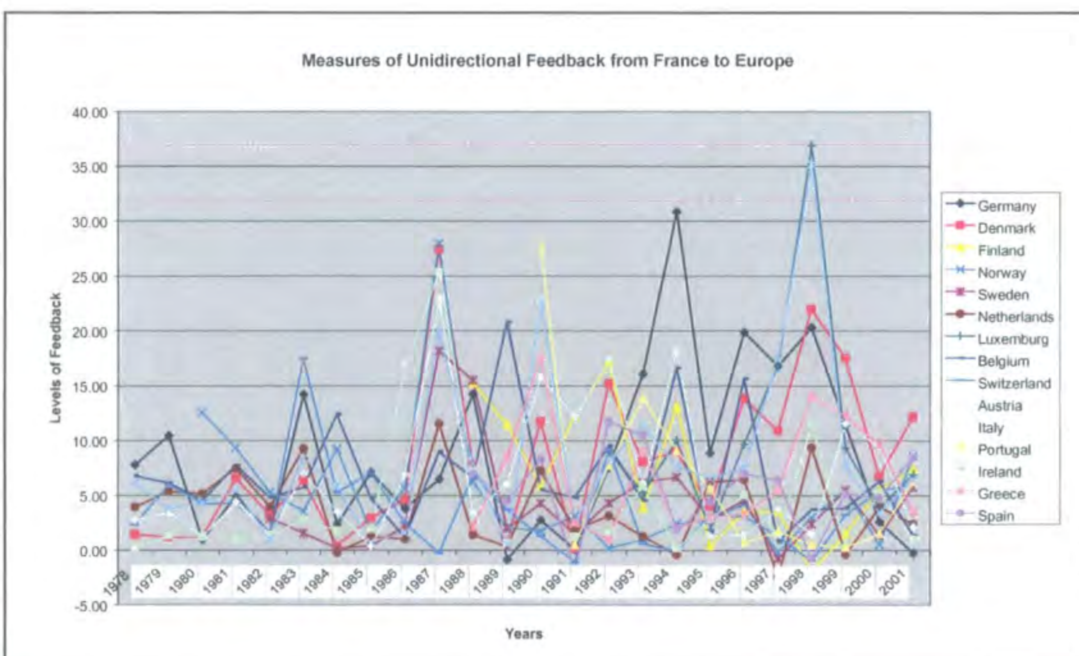
Year	Netherlands			Luxemburg			Belgium			Switzerland			Austria			Italy		
	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig
1978	3.89	0.27					6.75	0.08	*	2.32	0.51		2.74	0.43		0.33	0.95	
1979	5.31	0.15					6.09	0.11		5.92	0.12		3.45	0.33		1.29	0.73	
1980	5.13	0.16					4.49	0.21		4.20	0.24		1.19	0.76		1.21	0.75	
1981	7.43	0.06	*				7.69	0.05	*	4.26	0.23		4.39	0.22		1.04	0.79	
1982	3.90	0.27					4.77	0.19		1.52	0.68		1.38	0.71		1.32	0.72	
1983	9.23	0.03	**				5.68	0.13		17.44	0.00	***	6.96	0.07	*	2.76	0.43	
1984	-0.25	0.98					12.36	0.01	***	5.21	0.16		3.51	0.32		1.73	0.63	
1985	1.18	0.76					4.68	0.20		6.99	0.07	*	0.35	0.95		1.89	0.59	
1986	1.00	0.80					1.09	0.78		2.46	0.48		6.89	0.08	*	16.98	0.00	***
1987	11.52	0.01	***				8.93	0.03	**	-0.30	0.98		22.86	0.00	***	25.30	0.00	***
1988	1.38	0.71					6.59	0.09	*	6.80	0.08	*	3.34	0.34		7.23	0.06	*
1989	0.33	0.95					20.76	0.00	***	3.68	0.30		6.10	0.11		0.63	0.89	
1990	7.21	0.07	*				5.47	0.14		1.24	0.74		15.74	0.00	***	22.77	0.00	***
1991	1.89	0.60					4.76	0.19		-1.14	0.98		12.21	0.01	***	1.21	0.75	
1992	3.11	0.38		8.91	0.03	**	9.49	0.02	**	9.14	0.03	**	17.35	0.00	***	1.62	0.65	
1993	1.20	0.75		5.23	0.16		4.50	0.21		0.56	0.91		6.08	0.11		5.77	0.12	
1994	-0.44	0.98		10.01	0.02	**	16.56	0.00	***	-0.13	0.98		18.18	0.00	***	0.13	0.99	
1995	6.21	0.10		1.87	0.60		1.63	0.65		3.16	0.37		1.28	0.73		2.84	0.42	
1996	6.37	0.09	*	9.63	0.02	**	15.59	0.00	***	3.02	0.39		1.42	0.70		4.98	0.17	
1997	-2.46	0.98		16.78	0.00	***	0.74	0.86		1.25	0.74		3.69	0.30		1.43	0.70	
1998	9.34	0.03	**	36.84	0.00	***	3.67	0.30		-1.02	0.98		1.47	0.69		11.49	0.01	***
1999	-0.40	0.98		9.29	0.03	**	3.83	0.28		3.19	0.36		11.52	0.01	***	0.19	0.98	
2000	3.91	0.27		3.82	0.28		6.26	0.10	*	5.37	0.15		9.42	0.02	**	5.18	0.16	
2001	2.35	0.50		6.89	0.08	*	1.30	0.73		5.97	0.11		2.10	0.55		0.97	0.81	

Table 3.3.3ciii

Year	Italy			Portugal			Ireland			Greece			Spain		
	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig
1978	0.33	0.95					6.12	0.11							
1979	1.29	0.73					3.73	0.29							
1980	1.21	0.75					4.34	0.23							
1981	1.04	0.79					5.37	0.15							
1982	1.32	0.72					0.98	0.81							
1983	2.76	0.43					8.37	0.04	**						
1984	1.73	0.63					5.79	0.12							
1985	1.89	0.59					0.71	0.87							
1986	16.98	0.00	***				1.54	0.67							
1987	25.30	0.00	***				19.84	0.00	***						
1988	7.23	0.06	*				7.92	0.05	**	2.08	0.56		6.93	0.07	*
1989	0.63	0.89					0.44	0.93		8.47	0.04	**	4.46	0.22	
1990	22.77	0.00	***	27.67	0.00	***	22.56	0.00	***	17.47	0.00	***	8.22	0.04	**
1991	1.21	0.75		0.45	0.93		2.40	0.49		2.49	0.48		-1.92		
1992	1.62	0.65		7.66	0.05	*	8.00	0.05	**	0.90	0.83		11.65	0.01	***
1993	5.77	0.12		13.84	0.00	***	11.36	0.01	***	8.94	0.03	**	10.47	0.01	**
1994	0.13	0.99		9.01	0.03	**	7.59	0.06	*	2.00	0.57		1.88	0.60	
1995	2.84	0.42		5.67	0.13		6.53	0.09	*	2.97	0.40		4.31	0.23	
1996	4.98	0.17		0.68	0.88		7.44	0.06	*	3.22	0.36		6.90	0.08	*
1997	1.43	0.70		1.69	0.64		17.31	0.00	***	5.43	0.14		6.31	0.10	*
1998	11.49	0.01	***	0.49	0.92		35.14	0.00	***	13.99	0.00	***	-0.80	0.98	
1999	0.19	0.98		0.27	0.97		7.55	0.06	*	12.20	0.01	***	5.10	0.16	
2000	5.18	0.16		1.49	0.69		3.44	0.33		9.60	0.02	**	4.77	0.19	
2001	0.97	0.81		6.23	0.10		6.39	0.09	*	3.47	0.32		8.44	0.04	**

*Tables 3.3.3ci – 3.3.3ciii were estimated using equations (3.1) – (3.4) and (3.7) with France being country 1 and the other 15 European countries individually country 2; ***, ** and * denoting significance at 1%, 5% and 10%.*

Graph 3.3.3c: Tables 3.3.3ci, 3.3.3cii and 3.3.3ciii presented in graphical format



Looking at Figure 3.3.3c we also see the time varying nature of the levels of unidirectional feedback from France to Europe. Although the graph shows no clear pattern, we are able to see the dynamics of the levels impact from France to Europe across time. In terms of the impact on individual countries, the Paris bourse appears to affect Germany, Denmark and the Republic of Ireland the most. At least 54% of the statistic calculated for each of these countries is significant at conventional levels. This result is very important particularly in the case of Germany because of the size of the German stock market, its position in Europe and the extensive bilateral trade and other economic relationships between France and Germany. Effectively, our result is suggesting that the German stock market is informationally inefficient across days when compared to the French stock market. 58% of the calculated statistic for Germany is significant at the conventional levels. Compared to the results obtained for the UK for these three countries, the French stock markets affects the German and Danish stock more than the UK does and especially post 1998 in the case Denmark. The UK however appears to affect the Republic of Ireland stock market more than France does. The potential implication of this result is the possibility for the internationally informed investor to exploit this apparent inefficiency and earn abnormal profits.

Without over emphasising the implications of our results, if we compare the reported statistics for $\mathbf{H_3}$ (Table 3.3.3bi/ii/ii) with those reported for $\mathbf{H_2}$ (Table 3.3.3ci/ii/iii) for France and in particular those for the bilateral relationships between France and Germany, France and Denmark, and, France and the Republic of Ireland, we see that overall France commands the leading role in each of these bilateral relationships because level of rejection of $\mathbf{H_3}$ for these specific cases is more robust than the observed of $\mathbf{H_2}$. There is therefore sufficient evidence that, throughout our sample period, France affects the other 15 European countries more significantly than how the other markets affect France.

3.3.4 Germany Results

In this section we present results from our tests of capital market integration between Germany and fourteen European countries. From Table 3.3.1a we see that Germany has 14 unique pairings or combinations. As stated above, we study bilateral relationships in this way in order to avoid double counting. Again, as previously, the measures of contemporaneous or same day integration are chi squared distributed with 9 degrees of freedom and, the measures of unidirectional feedback or lead/lag relationships are chi squared distributed with 3 degrees of freedom. The measures of integration are calculated from equations (3.1) to (3.5) and for the measures of unidirectional feedback from equations (3.1) to (3.4) and (3.6) and, equations (3.1) to (3.4) and (3.7) respectively. In this analysis Germany will be Market one and the other 14 European countries will be Market two individually.

Table 3.3.4 Germany Integration and Unidirectional Feedback Results

Tables 3.3.4ai, 3.3.4aii and 3.3.4aiii: Measuring Integration between Germany and 14 European Countries on the same day - Geweke's Measure of Linear Dependence - distributed Chi Sq 9 df - This is the measure of contemporaneous relationship on the same day

Table 3.3.4ai

Year	Denmark Stats	P-Value	Sig	Finland Stats	P-Value	Sig	Norway Stats	P-Value	Sig	Sweden Stats	P-Value	Sig	Netherlands Stats	P-Value	Sig
1978	7.99	0.54											30.51	0.00	***
1979	9.85	0.36											43.49	0.00	***
1980	3.73	0.93					15.39	0.08	*				32.92	0.00	***
1981	13.19	0.15					21.06	0.01	**				33.16	0.00	***
1982	25.47	0.00	***				22.10	0.01	***	7.36	0.60		50.42	0.00	***
1983	5.26	0.81					24.71	0.00	***	10.35	0.32		39.69	0.00	***
1984	18.68	0.03	**				13.68	0.13		32.97	0.00	***	85.87	0.00	***
1985	6.79	0.66					20.51	0.01	**	4.79	0.85		33.46	0.00	***
1986	12.79	0.17					12.74	0.17		19.90	0.02	**	69.64	0.00	***
1987	34.13	0.00	***				120.98	0.00	***	135.72	0.00	***	205.81	0.00	***
1988	18.43	0.00	***	93.90	0.00	***	46.81	0.00	***	54.13	0.00	***	95.65	0.00	***
1989	57.53	0.00	***	48.19	0.00	***	94.87	0.00	***	105.85	0.00	***	119.86	0.00	***
1990	53.84	0.00	***	10.48	0.00	***	60.57	0.00	***	120.59	0.00	***	128.86	0.00	***
1991	147.34	0.00	***	25.47	0.00	***	117.23	0.00	***	100.56	0.00	***	165.84	0.00	***
1992	24.62	0.00	***	18.38	0.00	***	88.66	0.00	***	97.04	0.00	***	144.72	0.00	***
1993	15.85	0.00	***	13.56	0.00	***	53.20	0.00	***	43.64	0.00	***	109.11	0.00	***
1994	111.92	0.00	***	61.56	0.00	***	70.20	0.00	***	67.58	0.00	***	127.39	0.00	***
1995	55.60	0.00	***	68.42	0.00	***	64.60	0.00	***	56.44	0.00	***	109.12	0.00	***
1996	136.43	0.00	***	51.79	0.00	***	117.09	0.00	***	90.29	0.00	***	133.33	0.00	***
1997	183.58	0.00	***	207.40	0.00	***	146.92	0.00	***	203.30	0.00	***	251.01	0.00	***
1998	174.74	0.00	***	232.84	0.00	***	169.42	0.00	***	223.01	0.00	***	291.10	0.00	***
1999	70.65	0.00	***	108.12	0.00	***	125.11	0.00	***	123.62	0.00	***	274.81	0.00	***
2000	62.88	0.00	***	139.32	0.00	***	114.07	0.00	***	163.75	0.00	***	246.12	0.00	***
2001	63.10	0.00	***	69.96	0.00	***	61.80	0.00	***	111.45	0.00	***	140.29	0.00	***

*Estimated using equations (3.1) – (3.5) with Germany being country 1 and the other 16 European countries individually country 2. ***, ** and * denoting significance at 1%, 5% and 10%*

Table 3.3.4aii

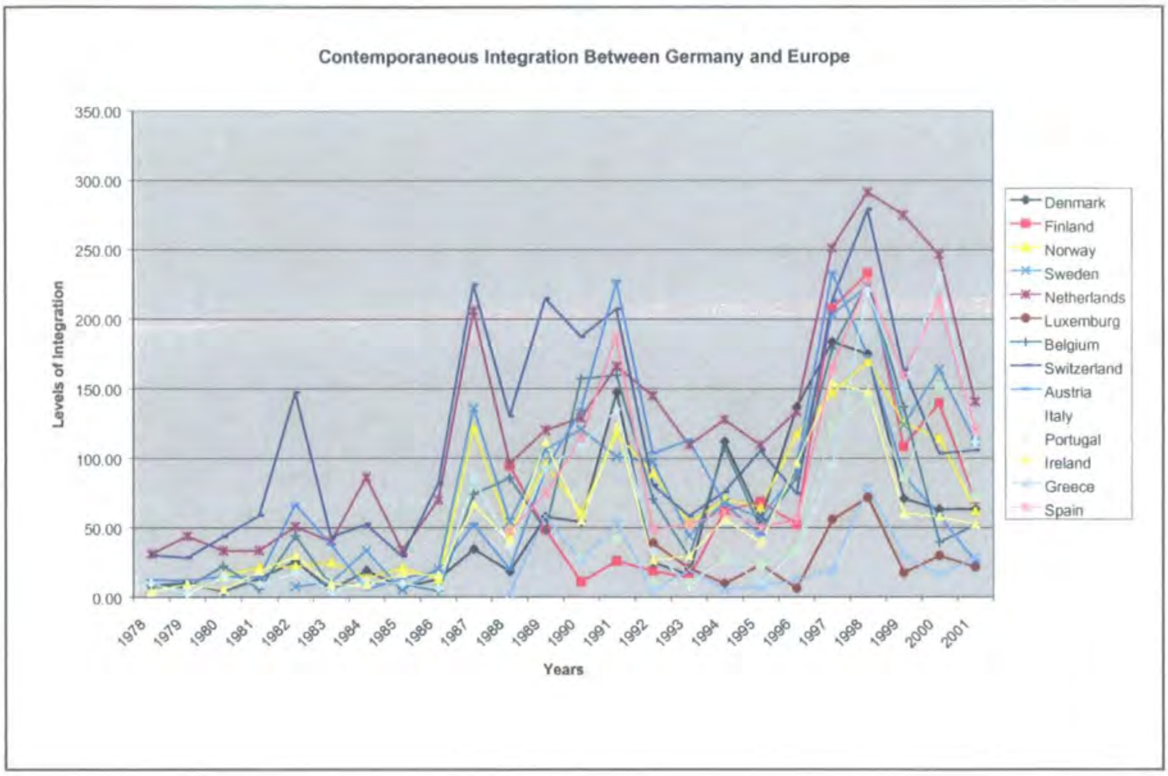
Year	Luxemburg Stats	P-Value	Sig	Belgium Stats	P-Value	Sig	Switzerland Stats	P-Value	Sig	Austria Stats	P-Value	Sig	Italy Stats	P-Value	Sig
1978				7.68	0.57		30.04	0.00	***	11.84	0.22		9.68	0.38	
1979				6.65	0.67		27.90	0.00	***	11.45	0.25		2.63	0.98	
1980				22.05	0.01	***	43.05	0.00	***	14.58	0.10		14.53	0.10	
1981				5.50	0.79		58.24	0.00	***	13.86	0.13		9.05	0.43	
1982				43.62	0.00	***	146.86	0.00	***	66.29	0.00	***	17.74	0.04	**
1983				7.41	0.59		43.13	0.00	***	37.63	0.00	***	4.31	0.89	
1984				10.20	0.33		52.17	0.00	***	5.07	0.83		11.19	0.26	
1985				9.17	0.42		29.03	0.00	***	13.09	0.16		9.47	0.40	
1986				4.00	0.91		81.53	0.00	***	18.59	0.03	**	6.26	0.71	
1987				73.81	0.00	***	224.48	0.00	***	52.17	0.00	***	85.15	0.00	***
1988				85.44	0.00	***	129.98	0.00	***	20.11	0.02	**	36.74	0.00	***
1989				47.97	0.00	***	214.56	0.00	***	91.45	0.00	***	92.35	0.00	***
1990				157.02	0.00	***	187.19	0.00	***	134.32	0.00	***	109.43	0.00	***
1991				159.50	0.00	***	207.07	0.00	***	226.79	0.00	***	134.86	0.00	***
1992	38.56	0.00	***	70.21	0.00	***	80.11	0.00	***	103.15	0.00	***	33.14	0.00	***
1993	20.46	0.02	**	28.49	0.00	***	58.00	0.00	***	112.63	0.00	***	7.52	0.58	
1994	9.50	0.39		107.35	0.00	***	75.43	0.00	***	66.66	0.00	***	28.20	0.00	***
1995	22.86	0.01	***	48.81	0.00	***	105.18	0.00	***	44.48	0.00	***	10.10	0.34	
1996	5.92	0.75		86.04	0.00	***	74.00	0.00	***	94.26	0.00	***	33.93	0.00	***
1997	55.47	0.00	***	178.40	0.00	***	213.13	0.00	***	233.41	0.00	***	94.87	0.00	***
1998	71.41	0.00	***	225.50	0.00	***	278.59	0.00	***	173.52	0.00	***	220.65	0.00	***
1999	17.21	0.05	**	136.79	0.00	***	163.55	0.00	***	87.41	0.00	***	149.81	0.00	***
2000	29.49	0.00	***	39.19	0.00	***	103.01	0.00	***	58.31	0.00	***	232.86	0.00	***
2001	21.40	0.01	**	51.44	0.00	***	105.30	0.00	***	25.24	0.00	***	111.33	0.00	***

Table 3.3.4aiii

	Portugal			Ireland			Greece			Spain		
Year	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig
1978				3.53	0.94							
1979				9.20	0.42							
1980				5.19	0.82							
1981				18.46	0.03	**						
1982				29.75	0.00	***						
1983				8.90	0.45							
1984				8.47	0.49							
1985				16.80	0.05	*						
1986				15.52	0.08	*						
1987				66.01	0.00	***						
1988				40.05	0.00	***	2.09	0.99		47.36	0.00	***
1989				111.04	0.00	***	57.88	0.00	***	73.85	0.00	***
1990	27.87	0.00	***	55.00	0.00	***	26.03	0.00	***	114.05	0.00	***
1991	42.56	0.00	***	122.34	0.00	***	52.85	0.00	***	186.72	0.00	***
1992	9.75	0.37		26.52	0.00	***	4.26	0.89		48.28	0.00	***
1993	10.24	0.33		29.78	0.00	***	19.36	0.02	**	51.75	0.00	***
1994	27.90	0.00	***	56.05	0.00	***	4.93	0.84		60.88	0.00	***
1995	22.96	0.01	***	39.35	0.00	***	6.91	0.65		49.89	0.00	***
1996	34.09	0.00	***	96.21	0.00	***	12.04	0.21		54.88	0.00	***
1997	123.95	0.00	***	153.90	0.00	***	18.92	0.03	**	163.91	0.00	***
1998	142.60	0.00	***	147.79	0.00	***	78.35	0.00	***	227.76	0.00	***
1999	86.02	0.00	***	60.42	0.00	***	29.58	0.00	***	159.42	0.00	***
2000	151.91	0.00	***	57.77	0.00	***	15.42	0.08	*	213.90	0.00	***
2001	70.80	0.00	***	52.27	0.00	***	28.33	0.00	***	119.94	0.00	***

*Both Tables 3.3.4aii and 3.3.4aiii were estimated using equations (3.1) – (3.5) with Germany being country 1 and the other 16 European countries individually country 2. ***, ** and * denoting significance at 1%, 5% and 10%*

Figure 3.3.4a - Tables 3.3.4ai, 3.3.4aii and 3.3.4aiii presented in graphical format: Contemporaneous integration between Germany and Europe 1978 - 2001



From the results in Table 3.3.4ai/ii/iii and the graph in Figure 3.3.4a we reveal the extent of contemporaneous or same day integration between Germany and fourteen European countries. From our tests of $\mathbf{H_1}$, we report a very strong contemporaneous relationship between Germany and the other countries. Over 83% of the calculated measures are significant at conventional levels. This is clear evidence that the German stock displays substantial co-movement with the other markets on the same day. The results generally mirror those obtained for the UK and France in their separate analysis for the similar set countries; they both displayed very strong contemporaneous integration on the same day with these countries. Also, looking at the graph in Figure 3.3.4a we see that the strength of integration between Germany and these countries increased considerably between 1986 and 1992, fell slightly between 1992 and 1996 and, have been increasing since the 1997 falling slightly in 2000 or 2001 in some cases. Figure 3.3.3a presents more or less a similar scenario for Frances' contemporaneous integration whilst Figure 3.3.2a portrays a somewhat different picture for the UK's measure of contemporaneous integration.

Further, Germany appears to portray an almost perfect integration with Netherlands, Switzerland and Spain. For these three countries and throughout the entire sample, we reject $\mathbf{H_1}$ outright, at the1% level of significance. For Portugal, Greece and Luxemburg, we report strong evidence integration prior to 1997. This result is different for the UK where there was no evidence of integration with these countries prior to 1997. Compared to France however, we reveal a similar pattern for the relationships with Portugal and Greece but a different pattern for the relationship with Luxemburg because we have evidence of contemporaneous integration between Germany and Luxemburg prior to 1997.

Once again, overall the results support the notion of international capital market efficiency – on the same day – because there is strong interdependence, which suggests that information is almost instantaneously transmitted between Germany and the other fourteen markets on the same day. We now present the results for the measures of unidirectional feedback from Europe to Germany.

Tables 3.3.4bi, 3.3.4bii and 3.3.4biii: Measuring Integration between Germany and 14 European Countries across days - Geweke's Measure of unidirectional feedback from Europe to Germany - distributed Chi Sq 3 df – This measures how Europe affects Germany across days

Table 3.3.4bi

Year	Denmark			Finland			Norway			Sweden			Netherlands		
	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig
1978	5.02	0.17											2.75	0.43	
1979	7.68	0.05	*										2.02	0.57	
1980	3.18	0.36					4.24	0.24					0.83	0.84	
1981	1.82	0.61					2.48	0.48					2.65	0.45	
1982	0.09	0.99					1.74	0.63		1.26	0.74		0.70	0.87	
1983	0.65	0.89					3.94	0.27		0.73	0.87		2.17	0.54	
1984	3.35	0.34					3.58	0.31		7.69	0.05	*	2.22	0.53	
1985	4.27	0.23					8.79	0.03	**	0.55	0.91		6.62	0.09	*
1986	0.13	0.99					5.66	0.13		1.12	0.77		0.87	0.83	
1987	2.09	0.55					1.11	0.78		-1.12		***	1.70	0.64	
1988	2.80	0.42		91.26	0.00	***	7.43	0.06	*	1.53	0.68		12.68	0.01	***
1989	0.09	0.99		5.66	0.13		6.34	0.10	*	15.85	0.00	***	-1.44		
1990	1.23	0.75		2.12	0.55		5.98	0.11		3.50	0.32		-0.27		
1991	1.09	0.78		1.13	0.77		7.21	0.07	*	1.33	0.72		6.23	0.10	
1992	2.32	0.51		4.99	0.17		1.07	0.78		8.74	0.03	**	3.73	0.29	
1993	3.95	0.27		3.79	0.29		2.32	0.51		23.23	0.00	***	9.89	0.02	**
1994	4.53	0.21		7.59	0.06	*	0.59	0.90		3.79	0.28		11.88	0.01	***
1995	5.25	0.15		10.53	0.01	**	3.00	0.39		17.70	0.00	***	8.47	0.04	**
1996	-0.19			7.40	0.06	*	5.12	0.16		16.66	0.00	***	10.49	0.01	**
1997	4.05	0.26		2.01	0.57		-2.75			26.79	0.00	***	25.60	0.00	***
1998	2.92	0.40		0.44	0.93		-3.02			2.58	0.46		0.19	0.98	
1999	4.73	0.19		1.19	0.76		2.89	0.41		4.10	0.25		1.81	0.61	
2000	2.68	0.44		-0.30			14.86	0.00	***	0.52	0.91		5.92	0.12	
2001	0.46	0.93		0.94	0.81		2.95	0.40		3.35	0.34		-1.41		

*Estimated using equations (3.1) – (3.4) and (3.6) with Germany being country 1 and the other 14 European countries individually country 2; ***, ** and * denoting significance at 1%, 5% and 10%.*

Table 4.3.4bii

Year	Luxemburg			Belgium			Switzerland			Austria			Italy		
	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig
1978				4.74	0.19		11.16	0.01	**	2.51	0.47		5.08	0.17	
1979				0.01	1.00		8.50	0.04	**	5.66	0.13		0.85	0.84	
1980				0.28	0.96		1.05	0.79		4.55	0.21		7.66	0.05	*
1981				1.17	0.76		3.36	0.34		0.87	0.83		1.05	0.79	
1982				6.66	0.08	*	-0.57			0.49	0.92		1.36	0.72	
1983				0.42	0.94		2.37	0.50		1.97	0.58		1.02	0.80	
1984				2.09	0.55		3.58	0.31		2.16	0.54		5.94	0.11	
1985				1.25	0.74		4.46	0.22		6.95	0.07	*	3.91	0.27	
1986				0.31	0.96		4.26	0.23		3.36	0.34		1.07	0.78	
1987				7.33	0.06	*	2.30	0.51		0.03	1.00		-0.01		
1988				-0.81			4.01	0.26		3.80	0.28		0.99	0.80	
1989				2.32	0.51		2.53	0.47		0.71	0.87		10.94	0.01	**
1990				-0.81			-0.16			4.63	0.20		3.81	0.28	
1991				4.48	0.21		4.94	0.18		2.55	0.47		-1.99		
1992	6.68	0.08	*	-0.46			5.25	0.15		1.93	0.59		3.03	0.39	
1993	9.17	0.03	**	0.49	0.92		3.33	0.34		3.54	0.32		1.95	0.58	
1994	1.79	0.62		3.67	0.30		6.20	0.10		3.25	0.35		3.39	0.34	
1995	0.62	0.89		1.77	0.62		6.64	0.08	*	1.14	0.77		6.21	0.10	
1996	2.38	0.50		0.54	0.91		6.75	0.08	*	-0.31			11.43	0.01	***
1997	-0.01			16.18	0.00	***	16.82	0.00	***	6.57	0.09	*	2.23	0.53	
1998	4.08	0.25		2.65	0.45		7.29	0.06	*	3.75	0.29		19.32	0.00	***
1999	0.57	0.90		2.17	0.54		4.68	0.20		3.33	0.34		11.24	0.01	**
2000	1.35	0.72		1.04	0.79		2.76	0.43		7.99	0.05	**	0.58	0.90	
2001	0.54	0.91		3.65	0.30		0.81	0.85		1.01	0.80		-0.26		

Table 3.3.4biii

	Portugal			Ireland			Greece			Spain		
Year	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig
1978				2.01	0.57							
1979				4.10	0.25							
1980				4.87	0.18							
1981				8.08	0.04	**						
1982				4.12	0.25							
1983				1.30	0.73							
1984				1.98	0.58							
1985				16.27	0.00	***						
1986				6.88	0.08	*						
1987				4.73	0.19							
1988				5.31	0.15		1.28	0.73		5.23	0.16	
1989				5.12	0.16		2.53	0.47		6.24	0.10	
1990	4.17	0.24		2.67	0.44		2.11	0.55		-0.76		
1991	0.40	0.94		-0.89			0.75	0.86		0.01	1.00	
1992	2.30	0.51		2.42	0.49		0.31	0.96		4.36	0.23	
1993	0.05	1.00		4.49	0.21		8.08	0.04	**	5.57	0.13	
1994	3.49	0.32		1.06	0.79		3.42	0.33		10.81	0.01	**
1995	2.12	0.55		6.15	0.10		0.58	0.90		17.62	0.00	***
1996	0.66	0.88		4.84	0.18		7.55	0.06	*	22.24	0.00	***
1997	1.69	0.64		2.36	0.50		5.19	0.16		32.01	0.00	***
1998	4.75	0.19		7.22	0.07	*	1.11	0.78		20.92	0.00	***
1999	0.13	0.99		0.06	1.00		2.04	0.57		5.90	0.12	
2000	1.39	0.71		13.51	0.00	***	0.04	1.00		0.08	0.99	
2001	0.42	0.94		0.15	0.99		0.67	0.88		1.24	0.74	

*Both tables estimated using equations (3.1) – (3.4) and (3.6) with Germany being country 1 and the other 14 European countries individually country 2; ***, ** and * denoting significance at 1%, 5% and 10%*

Figure 3.3.4b - Tables 3.3.4bi, 3.3.4bii and 3.3.4biii presented in graphical format:

Unidirectional Feedback form Europe to Germany 1978 - 2001

Table 3.3.4bi to 3.3.4biii and Figure 3.3.4b give the results for tests of unidirectional feedback from Europe to Germany (**H_2**). Our hypothesis is to test whether any of the fourteen European markets leads the German stock market across days. The results suggest a broad failure to reject **H_2** in most cases. Only 56 out of the 275 calculated measures were significant at conventional levels. This represents 20% of the calculated measures, which is a 6% more than over those reported for the UK and 1% more than those for France. We therefore provide evidence that events in European stock markets impact the German stock market more than how they affect the London stock exchange across days. In addition, European stock markets appear to have an identical effect on both France and Germany across days. This means that to some extent more markets lead Germany across days and the UK market in this respect evidently more efficient than the French and German stock market. This has implications for both the potential for earning abnormal returns and the construction of international portfolios including asset allocation decisions.

Although our results would tend to suggest that more European countries affect Germany across days compared to UK or France, the broad failure overall to rejects **H_2** for Germany is indicative of the leading role that the German stock market has over the other 14 European stock markets. In terms of the number of reported significant measures at conventional levels, the Swedish and Dutch stock markets affect the German stock market the most. However, the effect of the Swedish and Dutch stock markets on the German stock market is not as emphatic as the effects the French stock market has on the German stock market. Germany displays more bilateral inefficiency with France than with any other stock market in our sample. The behaviour of the Finnish stock market – especially in its maiden year – towards the German stock market is similar to those observed with both the UK and France. Looking at Figure 3.3.4b we again see this huge spike for Finland in 1988 followed by big a fall in the level of significance in 1989. The potential explanation for this has already been mentioned above.

Tables 3.3.4ci, 3.3.4cii and 3.3.4ciii: Measuring Integration between Germany and 14 European Countries across days - Geweke's Measure of unidirectional feedback from Germany to Europe - distributed Chi Sq 3 df – This measures how Germany affects Europe across days

Table 3.3.4ci

	Denmark			Finland			Norway			Sweden			Netherlands		
Year	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig	Stats	P-Value	Sig
1978	2.89	0.41											2.02	0.57	
1979	2.16	0.54											10.74	0.01	**
1980	0.43	0.93					2.21	0.53					3.57	0.31	
1981	5.87	0.12					1.67	0.64					1.08	0.78	
1982	0.99	0.80					1.37	0.71		3.42	0.33		1.81	0.61	
1983	0.31	0.96					0.26	0.97		0.98	0.81		-0.27		
1984	4.98	0.17					3.26	0.35		6.21	0.10		2.59	0.46	
1985	2.49	0.48					8.24	0.04	**	3.59	0.31		5.48	0.14	
1986	5.79	0.12					3.76	0.29		3.62	0.31		2.45	0.49	
1987	6.25	0.10	*				9.48	0.02	**	4.13	0.25		2.88	0.41	
1988	4.54	0.21		2.62	0.45		0.50	0.92		2.33	0.51		2.60	0.46	
1989	4.12	0.25		18.83	0.00	***	3.92	0.27		10.82	0.01	**	3.83	0.28	
1990	7.03	0.07	*	7.03	0.07	*	2.52	0.47		1.24	0.74		3.55	0.31	
1991	3.59	0.31		9.76	0.02	**	11.56	0.01	***	9.25	0.03	**	11.18	0.01	**
1992	4.67	0.20		7.09	0.07	*	0.75	0.86		-0.02			0.87	0.83	
1993	0.61	0.89		0.00	1.00		0.46	0.93		6.95	0.07	*	5.19	0.16	
1994	-1.02			1.31	0.73		0.85	0.84		2.67	0.44		1.09	0.78	
1995	7.14	0.07	*	5.47	0.14		2.68	0.44		4.52	0.21		1.90	0.59	
1996	2.90	0.41		3.39	0.34		11.23	0.01	**	9.34	0.03	**	5.67	0.13	
1997	11.23	0.01	**	1.61	0.66		6.10	0.11		9.73	0.02	**	11.70	0.01	***
1998	10.38	0.02	**	8.07	0.04	**	1.73	0.63		9.07	0.03	**	3.70	0.30	
1999	5.86	0.12		2.12	0.55		3.81	0.28		-1.95			4.09	0.25	
2000	8.05	0.05	**	6.05	0.11		4.55	0.21		3.99	0.26		1.40	0.71	
2001	16.86	0.00	***	4.74	0.19		7.28	0.06	*	1.69	0.64		0.65	0.88	

*Estimated using equations (3.1) – (3.4) and (3.7) with Germany being country 1 and the other 14 European countries individually country 2; ***, ** and * denoting significance at 1%, 5% and 10%.*

Table 3.3.4cii

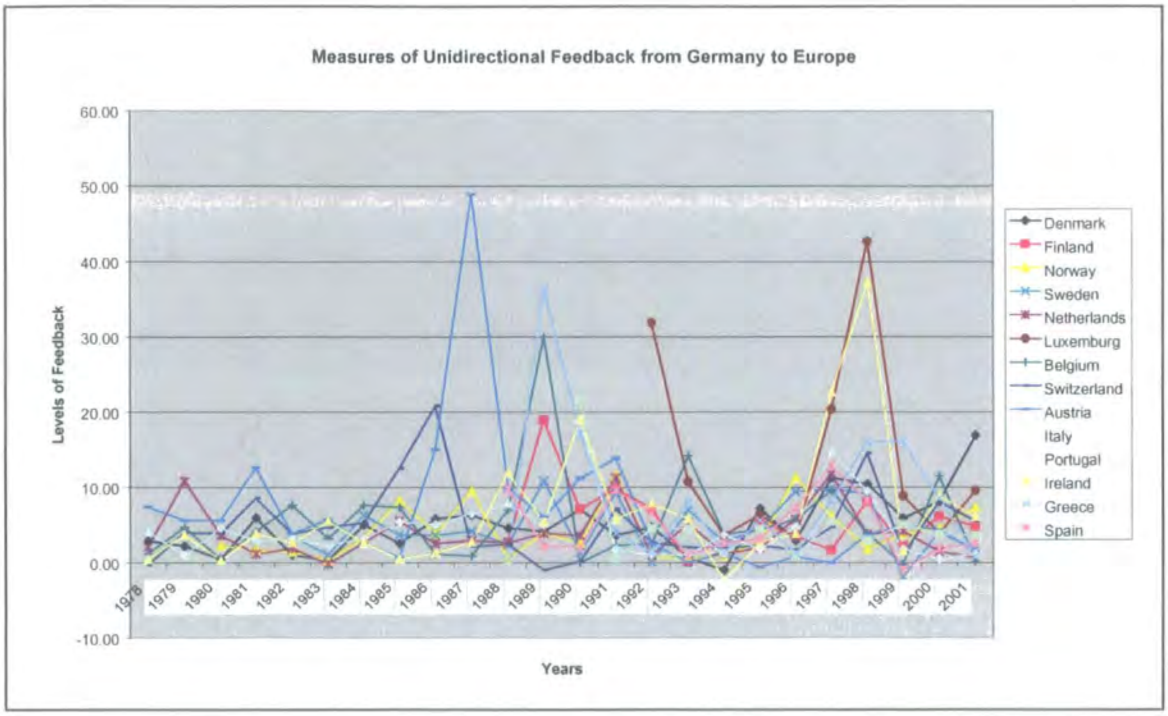
Year	Luxemburg Stats	P-Value	Sig	Belgium Stats	P-Value	Sig	Switzerland Stats	P-Value	Sig	Austria Stats	P-Value	Sig	Italy Stats	P-Value	Sig
1978				1.13	0.77		-0.34			7.35	0.06	*	4.03	0.26	
1979				4.59	0.20		3.95	0.27		5.55	0.14		0.95	0.81	
1980				0.33	0.95		3.80	0.28		5.54	0.14		4.55	0.21	
1981				4.08	0.25		8.49	0.04	**	12.55	0.01	***	2.88	0.41	
1982				7.57	0.06	*	3.79	0.29		3.79	0.28		3.04	0.39	
1983				3.13	0.37		4.65	0.20		5.70	0.13		2.30	0.51	
1984				7.54	0.06	*	5.22	0.16		2.47	0.48		3.16	0.37	
1985				7.27	0.06	*	12.48	0.01	***	0.67	0.88		5.33	0.15	
1986				1.11	0.77		20.76	0.00	***	14.94	0.00	***	5.07	0.17	
1987				0.81	0.85		2.07	0.56		48.83	0.00	***	6.44	0.09	*
1988				6.98	0.07	*	2.35	0.50		9.83	0.02	**	7.79	0.05	*
1989				29.93	0.00	***	-1.01			6.03	0.11		4.96	0.17	
1990				-0.03	0.98		0.12	0.99		11.14	0.01	**	18.97	0.00	***
1991				2.24	0.52		7.07	0.07	*	13.82	0.00	***	1.73	0.63	
1992	31.82	0.00	***	2.40	0.49		2.62	0.45		2.47	0.48		1.01	0.80	
1993	10.69	0.01	**	14.14	0.00	***	2.00	0.57		0.02	1.00		1.07	0.79	
1994	3.60	0.31		3.69	0.30		1.90	0.59		1.15	0.77		3.63	0.30	
1995	6.32	0.10	*	4.33	0.23		2.24	0.52		-0.66			1.73	0.63	
1996	3.28	0.35		5.64	0.13		1.62	0.66		0.69	0.88		4.65	0.20	
1997	20.30	0.00	***	9.49	0.02	**	4.68	0.20		-0.10			14.72	0.00	***
1998	42.63	0.00	***	3.82	0.28		14.48	0.00	***	3.65	0.30		9.46	0.02	**
1999	8.78	0.03	**	-0.28	0.98		1.18	0.76		4.90	0.18		1.75	0.63	
2000	3.85	0.28		11.49	0.01	***	8.04	0.05	**	4.26	0.24		0.48	0.92	
2001	9.53	0.02	**	0.11	0.99		5.44	0.14		1.40	0.71		1.07	0.78	

Table 3.3.4ciii

Year	Portugal Stats	P-Value	Sig	Ireland Stats	P-Value	Sig	Greece Stats	P-Value	Sig	Spain Stats	P-Value	Sig
1978				0.41	0.94							
1979				3.64	0.30							
1980				0.31	0.96							
1981				3.83	0.28							
1982				2.61	0.46							
1983				5.46	0.14							
1984				2.58	0.46							
1985				0.44	0.93							
1986				1.25	0.74							
1987				2.69	0.44							
1988				11.89	0.01	***	0.42	0.94		9.72	0.02	**
1989				5.41	0.14		36.24	0.00	***	2.12	0.55	
1990	21.69	0.00	***	19.07	0.00	***	17.09	0.00	***	1.89	0.60	
1991	0.56	0.91		5.78	0.12		3.88	0.27		9.59	0.02	**
1992	4.51	0.21		7.79	0.05	*	1.19	0.76		6.49	0.09	*
1993	4.44	0.22		5.82	0.12		7.93	0.05	**	0.93	0.82	
1994	1.13	0.77		-2.40			1.26	0.74		2.59	0.46	
1995	4.39	0.22		2.68	0.44		5.56	0.13		3.05	0.38	
1996	0.92	0.82		3.77	0.29		1.18	0.76		7.13	0.07	*
1997	5.40	0.14		22.81	0.00	***	8.10	0.04	**	12.72	0.01	***
1998	2.86	0.41		37.18	0.00	***	15.92	0.00	***	8.20	0.04	**
1999	5.00	0.17		1.50	0.68		16.08	0.00	***	-1.12		
2000	3.71	0.29		8.84	0.03	**	8.52	0.04	**	1.75	0.63	
2001	3.52	0.32		6.03	0.11		0.73	0.87		2.46	0.48	

*Both tables estimated using equations (3.1) – (3.4) and (3.7) with Germany being country 1 and the other 14 European countries individually country 2; ***, ** and * denoting significance at 1%, 5% and 10%.*

Graph 3.3.4c Tables 3.3.4ci, 3.3.4cii and 3.3.4ciii presented in graphical format: Unidirectional Feedback form Germany to Europe 1978 - 2001



In Table 3.3.4ci to 3.3.3ciii and Figure 3.3.4c above we give the results for the test (**H**$_3$) of the strength of unidirectional feedback from Germany to the other 14 European countries. Again, we test whether the German stock market leads the other 14 European stock markets across days. On average, we observe a general failure to reject **H**$_3$. There is some evidence that some of the other 14 European markets display information inefficiencies when compared with Germany although in most cases this is not clear-cut. We only reject, at conventional levels, 80 out of the 275 calculated measures of unidirectional feedback from Germany to Europe. This is equivalent to 29% of our calculated measures. Comparing this result to those obtained for the UK and France, for the same statistic: Germany has a decrease of 2 percentage points compared to the UK for which we reported 31% significant measures for H_3; compared to France on the other hand, Germany has a decrease of 10 percentage points due to the fact that 39% of the measures of $\mathbf{H_3}$ for France were significant at conventional levels. These results indicate that the UK stock market and the German stock have an almost identical leadership position over the other European stock markets but the French stock market has a higher leadership position because it leads more markets across days in percentage terms than the UK or Germany does. The increased efficiency of other European markets in their bilateral relationships with Germany is perhaps a testament to fact that Germany has a very important role in European integration and therefore all the other stock markets attempted to stay in tandem with events in Germany. Germany nonetheless has a higher leadership role over the other fourteen markets for which unidirectional feedback was measured.

From Figure 3.3.4c we also observe the time varying nature of the levels of unidirectional feedback from Germany to Europe. The graph shows the rate of change of the levels impact from Germany to Europe over the entire sample. With respect to the effects of Germany on the individual countries, the German stock market affects Belgium, Luxemburg and Greece the most. At least 50% of $\mathbf{H_3}$ for Luxemburg and Greece were significant at conventional levels and 33% of $\mathbf{H_3}$ reported for Belgium were also significant. For the remaining countries it is interesting to note that Germany had a profound effect on the Austrian stock prior to 1993. However, since 1993 the German stock market has not led the Austrian stock market. Given the proximity and relationship between the two countries this is reasonable evidence that the Austrian stock market has become more mature in its bilateral relationship with the German stock market since 1993 because it has shown no inefficiency in this period.

To summarise, the results from stage one of our analysis indicate that in general, the major stock markets in Europe – UK, France and Germany – commands a leading role over the other European countries in our sample. We also show that to a greater degree, all the markets in our sample are contemporaneously integrated on the same day. The results for stock market co-movements across days reveal some interesting details about the dynamics and levels of efficiency in the bilateral relationships between the markets. Although in general we can say that European stock market might be regarded as efficient because of the generally high significant statistics for $\mathbf{H_1}$ and the fewer significant statistics for $\mathbf{H_2}$ and $\mathbf{H_3}$, the fact that we have some evidence of significance for $\mathbf{H_2}$ and $\mathbf{H_3}$ shows that there are inefficiencies in the bilateral relationships between European stock markets and that these market may not be semi-strong efficient. The most surprising scenario was the discovery of the leadership role that the French stock market has over the German stock market. We now turn our attention to the dynamic panel data analysis of the relationship between co-movements in European stock markets and macroeconomic convergence in Europe.

3.3.5 Results from Dynamic Panel Data (DPD) Analysis

The nature of our dataset means that we have an unbalanced panel. An unbalanced or incomplete panel is where individuals in a panel data are observed over different sample periods. In this study there are seventeen countries with only ten of those countries having data for the entire sample (1978 – 2001). The other seven countries have shorter datasets of various lengths. Whilst we recognise the danger of potential selection bias in using incomplete or unbalanced panels, our estimation methodology and software are specifically formulated to handle such datasets[173].

We estimate equation (3.11) by implementing the GMM-type estimators introduced by Arellano and Bond (1991), Arellano and Bover (1995) and, Blundell and Bond (1998)[174]. Having tried different set of instruments and other instrumental variables estimators, the one and two-step GMM estimation and Combined System GMM produced the best estimates on the basis of key diagnostic tests – both the error serial correlation restriction and Sargan tests of over-identifying restrictions, which tests for the validity of the instruments, were satisfied. These GMM-type estimators are robust and eliminate bias and potential colinearities and heteroscedasticity in our DPD model. In particular, Monte Carlo experiments conducted by Blundell and Bond (1998) have shown that combined GMM system estimator reduces the potential biases in finite samples and asymptotic imprecision associated with the estimator first proposed by Arellano and Bond (1991)[175]. This augmentation was first proposed by Arellano and Bover (1995).

To our knowledge, this is the first application of application of dynamic panel data methods to tests of capital market and economic integration in Europe[176]. We

[173] All our DPD analysis is done in PcGive10.1 and according to Doornik, et al. (2000) DPD procedures in PcGive are expressly designed to handle unbalanced panels. See page 63 of Doornik, et al. (2000)
[174] Panel Data analysis in PcGive various types of estimators of which these are part of.
[175] Doornik, et al. (2000) also adjust for the downwardly biased standard errors produce by the asymptotic variance matrix computed in Arellano and Bond (1991) by implementing the small-sample correction derived by Windmeijer (2000). These produce robust standard errors.
[176] Beck, et al. (2000) used similar methods to assess the cross-country variance in economic growth and the sources of growth can be explained by the variance in the exogenous component of financial

present results for the two-step GMM in Table 3.3.3a for the relationship between the levels of contemporaneous integration and our selected macro economic measures and in Table 3.3.4b for the relationship between our combined measures of unidirectional feedback or integration across days and the proxy real activity variables. Verbeek (2000) and Baltagi (2001) lists consistency (robustness) and efficiency of instrumental variables estimators as the main advantages of using a DPD model[177]. The consistency of these estimators is guaranteed by the assumptions that the error terms in this model have no autocorrelation. This is a moment condition imposed by the instrumental variables/GMM-type estimator. We test for this in our models and is one of the criteria used to select the best model.

Despite not having all the macroeconomic variables[178] used in the BDK paper our DPD model represents a substantial efficiency gain in estimation because we are using instrumental variables/GMM-type estimator, which by their very nature are capable of reducing the potential collinearity problems noted in the BDK paper. In addition, Judson and Owen (1999), using Monte Carlo analysis, have shown that, for unbalanced panels, GMM-type estimators performs better especially when the time dimension of the panel is small. We also have a larger dataset and it gives us more degrees of freedom.

The results are presented in Tables 3.3.5a, 3.3.5b and 3.3.5c. Table 3.3.5a gives the result of the DPD analysis of the relationship between contemporaneous integration

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intermediary development. In a different but theoretically related way, Frankel and Rose (1997) used IV methods to assess economic integration in Europe.

[177] A review of GMM model is provided in the appendix to this chapter

[178] We have not used a measure of bilateral trade because of unavailability of the data and the peculiarities of our dataset. For example the bilateral trade data provided by Datastream was not available for most of the countries in our 136 pairs of markets. When

and macroeconomic convergence. The pooled measures of contemporaneous integration (H_1) for all the 136 unique pairings of seventeen countries is the dependent variable and, the lagged dependent variable and the selected macroeconomic variables are the independent variables. Of course, all the independent variables are also pooled for the 136 unique pairings. Table 3.3.5b does exactly the same analysis as in Table 3.3.5a but uses the absolute values of the macroeconomic variables. This specification was considered because of the suggestion in the BDK paper that the expected sign of these variables should be positive because "over a given year, greater divergence in inflation rates, real interest rates or currency valuation is likely to be associated with less co-movements across capital markets on the same day. We are agnostic about the sign of these variables and have therefore estimated both specifications. Table 3.3.5c reports the results of the combined DPD analysis of the relationship between the two measures of unidirectional feedback – $\mathbf{H_2}$ and $\mathbf{H_3}$ – and the selected macroeconomic convergence methods. We only report the result for the two-step GMM. In all the cases we investigated this provided the best results overall in terms of robust model diagnostics[179]. Our results are given below:

<u>Table 3.3.5a</u>

we included the available bilateral trade data in our DPD model our results were less robust in terms of the model diagnostics than when they were not included.

[179] Results for the One-step GMM and the combined GMM-SYS are available upon request.

Two-Step GMM

	Coefficient	Std.Error	t-value	t-prob
DINT(-1)	0.316191	0.04457	7.09	0.000
DINF_DIFF	153.102	70.48	2.17	0.030
DINF_DIFF(-1)	-252.503	74.43	-3.39	0.001
DRSTI_DIFF	82.1118	58.67	1.40	0.162
DRSTI_DIFF(-1)	-15.6209	58.75	-0.266	0.790
DLNEX	-3.53165	13.76	-0.257	0.798
DLNEX(-1)	15.0009	15.81	0.949	0.343
Constant	464.421	720.8	0.644	0.519

no. of observations 1340 no. of parameters 24
Using robust standard errors

Transformation used: first differences
Transformed instruments: INF_DIFF INF_DIFF(-1) RSTI_DIFF RSTI_DIFF(-1)
LNEX LNEX(-1)
Level instruments: Dummies Gmm(INT,2,99)

constant: yes time dummies: 16
number of individuals 136 (derived from year)
longest time series 17 [1984 - 2000]
shortest time series 3 (unbalanced panel)

Wald (joint):	Chi^2(7) =	83.79	[0.000]	**
Wald (dummy):	Chi^2(17) =	1223.	[0.000]	**
Wald (time):	Chi^2(17) =	1223.	[0.000]	**
Sargan test:	Chi^2(220) =	122.7	[1.000]	
AR(1) test:	N(0,1) =	-2.714	[0.007]	**
AR(2) test:	N(0,1) =	-0.1068	[0.915]	

**Significance at 1%

Table 3.3.5b

Two-Step GMM

	Coefficient	Std.Error	t-value	t-prob
DINT(-1)	0.336432	0.04345	7.74	0.000
Dabs_INF_DIFF	-136.474	96.23	-1.42	0.156
Dabs_INF_DIFF(-1)	-8.03225	72.22	-0.111	0.911
Dabs_RSTI_DIFF	-58.4248	60.82	-0.961	0.337
Dabs_RSTI_DIFF(-1)	145.017	64.12	2.26	0.024
Dabs_LNEX	-7.96385	16.29	-0.489	0.625
Dabs_LNEX(-1)	-17.2896	18.44	-0.938	0.349
Constant	458.920	991.5	0.463	0.644

```
no. of observations       1340  no. of parameters 24
Using robust standard errors

Transformation used:       first differences
Transformed instruments:  abs_INF_DIFF   abs_INF_DIFF(-1)
abs_RSTI_DIFF
  abs_RSTI_DIFF(-1)  abs_LNEX  abs_LNEX(-1)
Level instruments:         Dummies  Gmm(INT,2,99)

constant:                  yes  time dummies:  16
number of individuals      136  (derived from year)
longest time series         17  [1984 - 2000]
shortest time series         3  (unbalanced panel)

Wald (joint):    Chi^2(7)  =     83.63 [0.000] **
Wald (dummy):   Chi^2(17)  =     1063. [0.000] **
Wald (time):    Chi^2(17)  =     1063. [0.000] **
Sargan test:   Chi^2(220)  =     128.1 [1.000]
AR(1) test:        N(0,1)  =    -2.339 [0.019] *
AR(2) test:        N(0,1)  =    0.7803 [0.435]
```

**Significance at 1%

Table 3.3.5c

Two-Step GMM

```
                        Coefficient  Std.Error  t-value  t-prob
DINT22(-1)               -0.0495761    0.07545   -0.657   0.511
DINF_DIFF                  -17.5716      16.80    -1.05   0.296
DINF_DIFF(-1)              -9.34471      15.66   -0.597   0.551
DRSTI_DIFF                 -3.14565      9.954   -0.316   0.752
DRSTI_DIFF(-1)             -17.0294      10.89    -1.56   0.118
DLNEX                       7.21379      3.343     2.16   0.031
DLNEX(-1)                  -3.38030      2.468    -1.37   0.171
Constant                    16.4418      33.48    0.491   0.623

no. of observations         2680  no. of parameters 24
Using robust standard errors

Transformation used:       first differences
Transformed instruments:   INF_DIFF  INF_DIFF(-1)  RSTI_DIFF
RSTI_DIFF(-1)
  LNEX  LNEX(-1)
Level instruments:          Dummies  Gmm(INT22,2,99)

constant:                   yes  time dummies: 16
number of individuals       272 (derived from year)
longest time series          17 [1984 - 2000]
shortest time series          3 (unbalanced panel)

Wald (joint):     Chi^2(7)  =     13.25 [0.066]
Wald (dummy):    Chi^2(17)  =     112.2 [0.000] **
Wald (time):     Chi^2(17)  =     112.2 [0.000] **
Sargan test:    Chi^2(220)  =     209.2 [0.689]
AR(1) test:         N(0,1)  =    -2.239 [0.025] *
AR(2) test:         N(0,1)  =    -1.798 [0.072]
```

**Significance at 1%

We define INT as the measures of linear dependence or contemporaneous Integration – same day relationships – 2270 observations generated in stage 1; INT22 is the combined measure of unidirectional feedback or Integrations across days – a total of 4540 observation generated in stage one; INF_DIFF is the Inflation differentials between the pairs of countries; RSTI_DIFF is the Real Short-term interest rates differentials between the pairs of countries; LNEX is the log of the nominal bilateral exchange rates between the pairs of countries. Variables preceded by D imply a transformation in first difference, which is used as instruments for the variables in Levels.

The rational for using the selected macroeconomic variables as a proxy for the factors that influence bilateral trade relationship between two countries is a very simple one. If two markets are financially integrated, the level of bilateral trade relationship and macroeconomic convergence must be influential to their financial interdependence because movements in stock markets should generally reflect real activity. Financial deregulation and increased capital movements across markets would suggests that interest rates between countries should be moving in a more coordinated way, see for example the monograph by Marston (1995). We therefore hypothesise that for real convergence to be explained by macroeconomic convergence; real short-term interest rate differential must be positively related to co-movements in financial markets especially across days. We are partially agnostic about the relationship between real short-term interest rate differentials and financial interdependence on the same day. Although standard covered and uncovered interest rate parity conditions don't specifically require countries interest rates to move in a synchronous fashion, a significant decrease in their differentials should be expected if the markets are integrated. Given the results obtained in the previous section, there should be a negative relationship between the strong contemporaneous integration measures and the short-term interest rate differentials between the countries. These arguments are also consistent with our hypothesis or expected relationship between inflation differentials and levels or rate of change in bilateral exchange rates on the one hand, and levels of capital market integration on the other hand.

Before commenting on the results of the DPD model estimate we make some general comments on the specification of both models. The diagnostics from both table 3.3.3a and 3.3.3b shows that the model was well specified. The model was estimated using robust standard errors. There was no serial correlation in the residuals – our key moment condition – because the AR(1) test is significant and since the model is estimated in first difference this is evidence of no serial correlation in the residuals. The Wald tests in both models are as expected and are significant. This means that the individual (dummy) and time effects in these models are significant. Although the second model fails in the joint significance tests for all the parameters, the constants and all the time dummies were are significant in both models, which is good. The Sargan statistic for the validity of the extra instruments passes for both models. Overall, all of our DPD models are very well specified.

Results from the two-step GMM suggest that there is a positive relationship between contemporaneous integration (on the same) and the first lag of contemporaneous integration. This shows that we have a conditional mean value for the levels of contemporaneous integration – the current level of same day integration is a function of one lagged observation of contemporaneous integration. The model reveals no relation between the measures of co-movements across days and its lagged value. This is not surprising because the evidence of unidirectional feedback was not very strong. The result for the relationship between inflation differential and contemporaneous integration is positive for current differential and negative for first the first lag, of the inflation differential. A different result is obtained when we look at the absolute values of the measures of economic convergence – in other words when we are interested in the size of increase in economic convergence. We find that with this specification, the inflation differential is no longer significant but the lagged value of the real interest rate differential is now significant. In both specifications, the change in the nominal exchange rate does not affect the levels of contemporaneous integration.

These results for the relationship between contemporaneous integration and the variables that proxy for macroeconomic convergence shows that there is a slim possibility of exploiting the co-movements in European stock markets on the same day especially when there are noticeable changes in the levels of inflation differential or bilateral exchange rates between the countries. European markets are therefore better off in the increasingly global international financial arena if their macroeconomic policies with respect to inflation levels are pulled together. Otherwise, astute investors or speculators who are capable of exploiting potential profitable opportunities will do so. There was no relationship between the contemporaneous integration measure and the real short-term interest rate differential.

For co-movement across days, only the rate of change in bilateral nominal exchange rate was significant at conventional levels and the relationship is positive. This satisfies our hypothesis is that size of the change in bilateral change will induce more capital and trade flows between two countries thereby increasing the level of interdependence between the markets. This suggests evidence of lead/lag relationship between the markets across days. To discover the extent of these one has to look at the results of all the 136 unique pairing of the markets. In totality these results suggests that the three major markets in Europe UK, France and Germany tend to lead all the other markets with UK stock market having the greatest lead[180].

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[180] Full results are available on request

3.4 Conclusions

In summary, our results have revealed that there are significant co-movements between European stock markets (evidence of financial integration) on the same day rather than across days. This evidence is broadly consistent with international capital market efficiency although we do observe some levels of inefficiency. Our robust dynamic panel data analyses reveal that there is some explanatory power in the macroeconomic variables that proxy for the bilateral trade relationship between the pairs of countries investigated meaning that economic convergence can explain co-movements in financial markets. In general our results are consistent with some of the results in the studies by BDK and Campbell and Hamao (1992). They are also consistent with wider studies of multifactor asset pricing models, which suggest that economic variables have some explanatory power for stock returns, and those relating to the lead-lag relationships between financial markets[181]. The dynamic panel data techniques used in this study must be a welcome addition to previous research in this area. We also show that in an increasingly global financial environment effective financial interdependence must be supported by strong macroeconomic convergence.

[181] See for example Chen et. al. (1986) and Malliaris and Urruita (1992).

APPENDIX 3.1

Generalised Methods of Moments (GMM)

The current idea of the GMM is due to Hansen (1982). Good textbook exposition can be found in for example, Davidson and MacKinnon (1993), Hamilton (1994b), Johnston and DiNardo (1997) and Greene (2000). Research papers covering the subject include, Hansen and Singleton (1982), Hall (1993), Ogaki (1993), Ferson and Foerster (1994), Ferson and Harvey (1994), Newey and McFadden (1994), Harvey and Kirby (1996), Hansen and West (2002) and Jagannathan, et al. (2002)[182]. The collected volume by Matyas (1999) is also a good starting point.

The GMM is a method of moments (MOM) technique used to evaluate an equation or system of equations[183]. In particular, it provides a convenient way of determining the value of parameters under conditions which are less stringent. The GMM requires specification of only certain moment conditions instead of the full density of a distribution when estimating parameters. It also nests most of the common estimators such as, OLS, 2-stage least squares, linear and non-linear instrumental variables (IV) and maximum likelihood (MLE); and provides a framework for their evaluation and comparison. These qualities have made the GMM very attractive to researchers in economics.

[182] To commemorate the the twentieth anniversary of the publication of Hansen's paper on GMM, a special issue of the Journal Business and Economic Statistics devoted to the GMM was published in October 2002. It included interviews with Christopher A. Sims and Lars Peter Hansen. Anyone looking for an inspiration on original idea of the GMM should definitely read these interviews.

[183] The moments of a distribution are variables that describe the key characteristic of that distribution. The mean and the variance for example are the first and second moments of the normal distribution. Cryer (1986) described MOM techniques as one of the easiest and perhaps the most efficient method of obtaining parameter estimates. According to Cryer, the method consists of equating sample moments to theoretical moments and solving the resultant equation to obtain estimates of unknown parameters.

The GMM generalises the MOM technique to satisfy a general function of moments. This is represented by the orthogonality condition between the set of explanatory variables and the error vector. The population orthogonality condition is approximated by the sample orthogonality condition. Specifically, if the (y, X) are the data and θ is a set of parameters of the static model: $y = \alpha + X\beta + \varepsilon$; where $\theta = [\alpha\ \beta]$ and ε is the error vector, the population orthogonality condition is satisfied if , $\mathrm{E}\left[g(y, X, \theta)\right] = 0$; where $g(\bullet)$ is some continuous function of the data, (y, X), and the parameters, θ. The GMM employs the sample counterpart of the population orthogonality condition to estimate the parameters of a model. For a given sample, the GMM estimator of the parameter set θ, is the value of θ, defined as θ_{GMM}, that minimises the following with respect to θ_{GMM} :

$$m(y, X, \theta_{GMM})' \cdot W_n^{-1} \cdot m(y, X, \theta_{GMM}) \qquad \textbf{(3.4.1)}$$

Where $m(y, X, \theta_{GMM}) = (1/n)\sum_1^n g(y_i, X_i, \theta)$, and W_n is a function of the data that converges in probability to some matrix W, that is symmetric and positive definite. Johnston and DiNardo (1997) have shown that the GMM estimator is consistent only if, in the limit, the true value of the parameters θ, minimises the above function (3.41) and suitable regularity conditions hold – these are technical conditions that ensures the asymptotic results. The fist order condition for minimum can be written as:

$$\left\{ \frac{\partial m(y, X, \theta)}{\partial \theta'} \bigg|_{\theta = \theta_{GMM}} \right\}' \times W_n^{-1} \times \left[m(y, X, \theta_{GMM}) \right] = 0 \quad \textbf{(3.4.2)}$$

Analytically, the W_n, the weighting matrix, is an estimate of the matrix W, where, $W = \lim_{n\to\infty}(1/n)\sum_{t=1}^{n}\sum_{v=-\infty}^{\infty} \mathrm{E}\left\{\left[g(y_t, X_t, \theta)\right]\left[g(y_{t-v}, X_{t-v}, \theta)\right]'\right\}$. The GMM estimate can be treated as if $\theta_{GMM} \sim N\left(\theta, \left(D'\Omega D\right)^{-1}\right)$; where $D = \partial m(y, X, \theta)/\partial\theta'$ and $\Omega = \mathrm{E}\left[g(\bullet)\, g(\bullet)'\right]$; and is the variance of the moment conditions.

Hamilton (1994b) and Johnston and DiNardo (1997) derive the distribution of the standard GMM estimator and illustrate the special cases where the GMM estimator is equivalent to OLS, IV and MLE. It has also been shown that the estimate of the weighting matrix W_n is equivalent to a Newey and West (1987) or a White (1980) covariance matrix[184]. These estimators provide a way of calculating consistent covariances matrices when the conditions for serial correlation and heteroscedasticity are violated. We will not reproduce all of these proofs here. Another important aspect of GMM estimation is the testing of identifying restrictions if a system of equation is being evaluated. The number of orthogonality conditions and the number of unknown parameters determine whether the system is over-identified. A system is over-identified if the number orthogonality conditions exceed the number of unknown parameter. This implies that the system is being evaluated with more orthogonality conditions than is required for number of unknown parameters. This can be investigated by using Hansen (1982) J-test[185].

There are advantages and disadvantages of using the GMM. The GMM is a distribution-free estimator, thus, GMM is based on less restrictive assumptions than

[184] See Davidson and MacKinnon (1993) and Hamilton (1994b).
[185] See Hamilton (1994b). The J-test is equivalent to the minimised value of the GMM objective function multiplied by the sample size. This is a chi-square test with degrees of freedom equal to the overidentifying restrictions.

ML for example – GMM does not require normally distributed errors. GMM is based on orthogonality conditions, which allows for the incorporation of the notion that financial market participants incorporate all information (the instruments, if we use instrumental variable estimation) into the model. The main disadvantage of GMM is that it is not efficient when the distribution is known. For example, when the errors are normally distributed the ML estimator is more efficient than GMM, as the latter is based on a distribution free approximation of the true distribution via the central limit theorem and the former employs the true distribution.

CHAPTER FOUR

AN EXAMINATON OF THE COMOVEMENTS IN INTERNATIONAL EQUITY AND BOND MARKETS

4.1 INTRODUCTION

Understanding the comovements in international equity and bond markets is crucial for international financial and monetary stability. Asset return covariances are key inputs in the construction of portfolios for investors wishing to diversify, and is therefore crucial to international asset allocation decisions. In Chapter 2 we report evidence which shows that variations in the macroeconomy are reflected in the variations in financial asset prices. Rigobon and Sack (2003)[186] have shown that there is a significant policy response from monetary authorities when there is a five-percentage point change in the stock market. From a practitioners viewpoint, in their annual publication – the Global Financial Stability Report; the International Monetary (IMF) publishes various reviews on this subject providing an assessment of the threats to the international financial system including the likely effects of financial instability. Most central banks and national financial regulatory bodies of industrialised countries continuously monitor the developments in international financial markets in order to insulate their respective financial systems from the effects of financial crises or to prevent systemic risks. The second core purpose of the Bank of England, for example, is to maintain the stability of the domestic and

[186] This paper was initially circulated as NBER working paper in 2001. Similar views are expressed in Forbes and Rigobon (2002)

international financial system[187]. It seeks to achieve this, in part, through monitoring the developments in the financial system both at home and abroad, including links between institutions and financial markets.

This chapter contributes to this debate by developing a methodology of decomposing the effects of shocks across international equity and bond markets, and test for market integration. Specifically, the chapter seeks to determine the extent to which equity and bond markets are influenced by common factors. The degree of influence would capture the dynamic nature of capital market integration between countries, and the commonality of exposures between the markets. The levels and validity of the residual factor determines the extent of capital market integration. We are also interested in exploring jointly, the extent to which equity and bond markets are driven by common shocks and the levels of spillovers between these markets; which has implications for financial stability. In totality, answers to these questions would yield the following results. First, our analysis could be regarded as a new tool for measuring capital market integration. The approaches used here can be used as a financial stability monitoring tool, and for constructing international portfolios investments in equity and bonds. In general, understanding the differential nature of the comovements in equity and bond markets is important for international asset pricing and capital market integration

We unlock the dynamic relationship between international equity and bond markets and assess the extent of spillovers or contagion between these markets in restricted dynamic factor modelling framework. Our methodology combines an observable

[187] The first core purpose to maintain the integrity and value of the currency, above all by maintaining price stability and the third is to ensure the effectiveness of the UK's financial services. See the Bank of England website: www.bankofengland.co.uk

and a latent variable structure. Instead of focussing entirely on the loadings, we decompose the total variation in the system into a number of differential effects.

The methodology builds on existing factor models found in the literature. A number of factor models have been suggested by the following: Connor and Korajczyk (1988), Diebold and Nerlove (1989) Stock and Watson (1991), Campbell and Hamao (1992), Fama and French (1993), King, et al. (1994), Lin, et al. (1994), Dungey (1999) and Dungey, et al. (2000). The review conducted in chapter 2, noted that most of the academic research in the aftermath of the stock market crash of October 1987 suggested that economic agents did not adequately decompose the effects of economic news or information emanating from overseas. The approach we propose addresses this point through the various decompositions that we suggest. The methodology would be very useful for those involved in financial stability monitoring. Section 2 outlines the estimation methodology. Section 3 describes the data and conducts preliminary econometric analysis. Section 4 discusses the empirical results and section 5 concludes.

4.2 Methodological Issues

Multifactor models are very popular in empirical finance. They have been used to predict returns, generate estimates of abnormal returns and estimate the variability and covariability of asset returns. For our purposes we focus on the use of factor models to describe the covariance structure of international equity and bond returns[188]. A factor model decomposes an asset returns into a common component – common to all assets and capturing fundamental risk characteristics; and an idiosyncratic component – specific to a particular asset and capturing asset specific risks. Factor loadings or sensitivities are computed for these components. There are three main types of factor models in the empirical finance literature: macroeconomic factor modes; fundamental factor models; and statistical factor models. Macroeconomic factor models, for example Chen, et al. (1986), use observable economic variables such as GDP, inflation or interest rates to capture the pervasive or common variation in asset returns. Fundamental factor models, for example Fama and French (1993), use observable idiosyncratic variables fundamental to a firm such as, firm size, book-to-market ratio, dividend yield, earnings-price ratios or industry classifications to capture the common component in asset returns. Statistical factor models, for example Roll and Ross (1980) and Connor and Korajczyk (1993), treats the pervasive common factors as unobservable or latent factors[189]. This chapter combines both the macroeconomic and statistical factor model to estimate a restricted dynamic factor model for international stock and bond markets. The intuition behind our structure is similar in sprit to approach taken by Burmeister and McElroy (1988) 'who augment statistical factors with a market portfolio and illustrate how to "rotate" the factors, to interpret them relative to more intuitive economic variables'(Ferson (2003)).

We suggest a two-stage analysis for our dynamic factor model. In stage one, asset returns are filtered or demeaned by regressing on an observables global common factor – the world market portfolio. This observable global factor is interpreted as

[188] Connor (1995), Ferson (1995), Chan, et al. (1998) Elton, et al. (1999), Cochrane (2001) and Ferson (2003) provide an excellent review of factor pricing models.
[189] There are a various methods of conducting standard and non-standard statistical factor analysis. See for example, Chamberlain and Rothschild (1983), Dhrymes, et al. (1984), Connor and Korajczyk (1986), Jones (2001), Bai and Ng (2002), Xu (2003), Kapetanios and Marcellino (2003).

capturing fundamental risks components or pervasive common factor[190]. The output from stage one is the demeaned or residual return. Stage two models the residual return as a restricted dynamic latent factor model. The restrictions are due to an additional observable factor introduced to capture regional variations across international equity and bond markets and also to capture contagion effects across the asset markets. The extent of capital market integration across equity and bond markets is measured by the size of the idiosyncratic component. If there remains a larger variation in the idiosyncratic component in percentage terms, this suggests that the markets are segmented. To test whether the idiosyncratic factor is truly idiosyncratic, we extract these factors and assess the significance of the idiosyncratic correlation matrices. The methodology is outlined more formally below:

4.21 A Factor model of equity and bond returns

The estimation methodology is a two-stage process. In stage one we hypothesise that the return generating process of equity and bond returns is captured by the following equation:

$$r_t = \alpha + \beta W_t + \delta L_t + r_t^* \qquad \textbf{(4.21)}$$

where the dependent variable is the observed asset return at time t, W represents the return on the observed world factor and L represents the return on the observed local factor. The residuals of the regression, r^*, are free from observed world and local market effects. Details of the factors are provided in the next sub-section.

[190] We initially included an observable local factor – the dividend yield on the domestic stock market and the GDP. The explanatory powers of these were inconsistent across the panel of countries. These were therefore dropped.

In stage two the filtered (residual) return are modelled as a restricted latent factor model. The basic latent factor model, in matrix notation, takes the following general form[191]:

$$r^{*} = \mathrm{B}F + e \qquad \textbf{(4.22)}$$

where

$r^{*} = p$-dimensional vector of observed returns, $r^{*\prime} = (r_1^{*}, r_2^{*}, \cdots, r_p^{*})'$

$F = q$-dimensional vector of latent factors common factors, $F' = (f_1, f_2, \cdots, f_q)'$

$e = p$-dimensional vector of idiosyncratic returns, $e' = (e_1, e_2, \cdots, e_p)'$

$\mathrm{B} = p \times q$ matrix of factor loadings,

$$\mathrm{B} = \begin{pmatrix} \lambda_{11} & \lambda_{12} & \cdots & \lambda_{1q} \\ \lambda_{21} & \lambda_{22} & \cdots & \lambda_{2q} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{1p} & \lambda_{2p} & \cdots & \lambda_{pq} \end{pmatrix}$$

For the identification of the factor model, the following additional assumptions are also required:

i. The idiosyncratic factors and common factors are uncorrelated, $\mathrm{cov}(e, f') = 0$

ii. The idiosyncratic factors are uncorrelated with each other, $\mathrm{E}(ee') = \Psi = \begin{pmatrix} \psi_1 & \cdots & \mathbf{0} \\ \vdots & \ddots & \vdots \\ \cdots & \cdots & \psi_{\mathrm{p}} \end{pmatrix}$

iii. The latent factors are orthogonal, $\mathrm{E}(ff') = \mathrm{I}$

Based on these assumptions, the variance-covariance matrix of the observed returns is given by, $\Sigma = \mathrm{BB}' + \Psi$ [192]. When the number of common factors is equal to the

[191] Extensive discussions on basic factor modelling can found in Anderson (1984) and Morrison

number of variables, the matrix of factor loadings is equal to the variance-covariance matrix, i.e. $\Psi = 0$. In empirical factor modelling the idea is to explain the covariance structure of assets by a small number of common factors. The covariance structure of asset returns is therefore approximated: $\sum \approx BB' + \Psi$ =

$$= \begin{bmatrix} \sqrt{\lambda_1 \gamma_1} & \sqrt{\lambda_2 \gamma_2} & \cdots & \sqrt{\lambda_p \gamma_q} \end{bmatrix} \begin{bmatrix} \sqrt{\lambda_1 \gamma_1} \\ \sqrt{\lambda_2 \gamma_2} \\ \vdots \\ \sqrt{\lambda_q \gamma_q} \end{bmatrix} + \begin{bmatrix} \psi_1 & 0 & \cdots & 0 \\ 0 & \psi_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \psi_q \end{bmatrix}$$

where $\lambda_1, \lambda_2 \cdots, \lambda_q$ are the first q eigenvectors of $\sum$ and $\gamma_1, \gamma_2 \cdots, \gamma_q$ are the corresponding eigenvectors. Factor modelling could therefore be viewed as a variance-covariance modelling exercise. To estimate the matrix of factor loadings, B, we simply use the decomposition of the variance-covariance matrix given above. A number of methods can be used to decompose the variance-covariance matrix. Gaussian maximum likelihood (ML) and principle component analysis (PCA) are the most widely used. ML has the advantage of selecting the maximum number of relevant common factors. ML is however less robust to the departures from normality in the data. PCA is dimension reduction technique is robust to departures from normality. The disadvantage of PCA is the lack of reliable statistical criterion for selecting the maximum number of factors. We rely on economic intuition to accomplish this.

The methodology adopted in this chapter focuses on the contribution of each factor to overall variance. Because of the potential problems of using ML or PCA we estimate our model using the GMM estimation methods. The full structure of our model is provided in the next sub-section.

(1990).

4.22 A restricted factor model of equity and bond returns

The structure of the restricted factor model developed in this section draws on King, et al. (1994), Dungey (1999), and Dungey, et al. (2002). Equity and bond returns are expressed as follows:

$$r_{it} = \overbrace{\alpha_i + \beta_i W_t + \delta_i L_{it}}^{\text{observed factors}} + \overbrace{\lambda_i C_t + \gamma_i R_{kt} + \phi_i f_{it}}^{\text{unobserved factors}} \qquad i = 1,\ldots,n \qquad k = US, Eur$$

(4.23)

Each equity and bond return is presumed to evolve in response to movements in a number of observed factors, W_t and L_{it} respectively, a time-varying common unobserved factor, C_t, a time-varying unobserved regional factor, R_{kt} and a time-varying residual factor, f_{it}. The unobserved factors are each specified as stationary and independent disturbance processes[193]. The time-invariant loadings on these factors vary across countries and are given by the parameters β_i, δ_i, λ_i, γ_i and ϕ_i. The restricted form allows to separate the unobserved factors relating to the entire set of markets, the regional (US and European) groupings and to the individual returns.

This model (4.23) is a combined form of equation (4.21) and (4.22). We include a world market returns and a number of local factors as proxies for the observed factors. For equity returns, the world stock market index, the dividend yield on the domestic stock market index and GDP were considered. Initial analysis suggests

[192] Alternatively, the correlation matrix can be used if the observed returns are standardised.

[193] The equity returns and change in bond price of each country are stationary and so compatible with the factor specification. Dungey, et al. (2000) and Dungey and Martin (2002) show how this model can be extended to deal with GARCH-type effects at the cost of a huge increase in estimation time.

that for national stock markets, only the observed world stock market index was significant[194]. We therefore decided to exclude all the other local factors. The observed world factor can be viewed as a proxy for the variation in observable macroeconomic variables that explain the variation in G10 equity returns. For bond returns, only the unfiltered returns were. The world bond index series was not long enough to be included in our analyses. The following final version of the model is estimated with all variables remaining as previously defined:

$$r_{it} = \overbrace{\alpha_i + \beta_i W_t}^{\text{observed factors}} + \overbrace{\lambda_i C_t + \gamma_i R_{kt} + \phi_i f_{it}}^{\text{unobserved factors}} \qquad i = 1,\ldots,n \qquad k = US, Eur \qquad \textbf{(4.24)}$$

The model is estimated in two stages. First, the returns are regressed on the observed factor and a constant, using robust error estimation. The R^2 of each regression gives the proportion of equity returns variance explained by the observed factor. The residuals of these regressions are then used in the second stage unobserved restricted factor model. The restricted latent factor model takes following the form:

$$\begin{bmatrix} r_1^* \\ r_2^* \\ \vdots \\ r_n^* \end{bmatrix} = \begin{bmatrix} \lambda_1 & I_1\gamma_{US1} & (1-I_1)\gamma_{EU1} & \phi_1 & 0 & \cdots & 0 \\ \lambda_2 & I_2\gamma_{US2} & (1-I_2)\gamma_{EU2} & 0 & \phi_2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \lambda_n & I_n\gamma_{USn} & (1-I_n)\gamma_{EUn} & 0 & 0 & \cdots & \phi_n \end{bmatrix} \begin{bmatrix} C \\ R_{US} \\ R_{EU} \\ f_1 \\ f_2 \\ \vdots \\ f_n \end{bmatrix} \quad \text{or} \quad r^* = BF \qquad \textbf{(4.25)}$$

where r^* is the $N \times 1$ vector of stacked residual equity or bond returns, F is an $(N + 3) \times 1$ vector of latent factors and B is an $N \times (N + 3)$ matrix of coefficients

[194] Although traditional forecasting variables such as dividend yield have been found to predict stock returns, this finding is consistent with some of the latest research in the asset return predictability literature. See for example Bossaerts and Hillion (1999), Ang and Bekaert (2003) and Goyal and Welch (2003).

attached to the factors, some of which are restricted to zero. I_i denotes an indicator variable for each country that takes the value unity if the asset return is US-based and zero otherwise. It follows that:

$$\operatorname{var}\left(r^*\right) = B \operatorname{var}(F) B' \qquad \textbf{(4.26)}$$

The variance-covariance matrix var(r^*) will have $N(N + 1)/2$ unique elements. Using these moment conditions we can identify at most $N(N + 1)/2$ parameters from the system of equations. There are N parameters relating to the loadings on the common factor, N factors relating to regional factors and N loading parameters on the residual factors. These moment conditions plus the assumption that var(F) = I_{N+3} produces the necessary identifying condition that $N \geq 5$; equity or bond returns for at least five countries are necessary to estimate the system. The assumption that var(F) = I_{N+3} is necessary since var(F) is unobserved. To the extent that this assumption is violated, the parameter estimates will absorb the true variance of the factors meaning that comparing the magnitudes of the factors is uninformative. However, the following decomposition of the unconditional variance is unaffected:

$\frac{\lambda_i^2}{\operatorname{var}(r_i^*)}$ = contribution of the common factor to variance of residual equity or bond returns of country i

$\frac{\gamma_i^2}{\operatorname{var}(r_i^*)}$ = contribution of the regional factor to variance of residual equity or bond returns of country i

$\frac{\phi_i^2}{\operatorname{var}(r_i^*)}$ = contribution of the idiosyncratic factor to variance of residual equity or bond returns of country i

We are also interested in the joint behaviour of G10 markets asset prices. A restricted latent factor model is jointly estimated for equity and bond markets. The intuition here is for us to be able to capture the joint comovements or interaction between the equity and bond market. This multivariate structure will specifically allow us to identify potential spillovers between the equity and bond market. The model is given below:

$$\begin{bmatrix} re^*_{1t} \\ \vdots \\ re^*_{nt} \\ rb^*_{1t} \\ \vdots \\ rb^*_{nt} \end{bmatrix} = \begin{bmatrix} \lambda^E_1 \\ \vdots \\ \lambda^E_n \\ \lambda^B_1 \\ \vdots \\ \lambda^B_n \end{bmatrix} C_t + \begin{bmatrix} \delta^E_1 & 0 \\ \vdots & 0 \\ \delta^E_n & 0 \\ 0 & \delta^B_1 \\ 0 & \vdots \\ 0 & \delta^B_n \end{bmatrix} \begin{bmatrix} M^E_t \\ M^B_t \end{bmatrix} + \begin{bmatrix} I_1\gamma^E_{US1} & (1-I_1)\gamma^E_{EU1} \\ \vdots & \vdots \\ I_n\gamma^E_{USn} & (1-I_n)\gamma^E_{EUn} \\ I_1\gamma^B_{US1} & (1-I_1)\gamma^B_{EU1} \\ \vdots & \vdots \\ I_n\gamma^B_{USn} & (1-I_n)\gamma^B_{EU1} \end{bmatrix} \begin{bmatrix} R^{US}_t \\ R^{EU}_t \end{bmatrix}$$
$$+ \begin{bmatrix} \phi^E_1 & \cdots & 0 & 0 & \cdots & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & \phi^E_n & 0 & \cdots & 0 \\ 0 & \cdots & 0 & \phi^B_1 & \cdots & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & 0 & \cdots & \phi^B_n \end{bmatrix} \begin{bmatrix} f^E_{1t} \\ \vdots \\ f^E_{nt} \\ f^B_{1t} \\ \vdots \\ f^B_{nt} \end{bmatrix} \qquad (4.27)$$

The dependent variables are now a column of equity returns purged of world market effects and the bond returns. These depend upon four types of unobserved factors. A common factor, C_t, affects both stock and bond markets but with loadings that vary across countries and asset class. Two market factors, M^E_t, equity markets and M^B_t, bond markets, affect each asset class independently. Regional factors R^{US}_t and R^{EU}_t, affect both asset classes of the markets in a region but with different loadings across both markets and asset class. Finally the idiosyncratic factors, f_t, specific to each asset of each country capture the rest of the variation in the dependent variable. The multivariate system estimated is of the following form:

$$\begin{bmatrix} re^*_{1t} \\ \vdots \\ re^*_{nt} \\ rb^*_{1t} \\ \vdots \\ rb^*_{nt} \end{bmatrix} = \begin{bmatrix} \lambda_1^E & \delta_1^E & 0 & I_1\gamma_{US1}^E & (1-I_1)\gamma_{EU1}^E & \phi_1^E & \cdots & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \lambda_n^E & \delta_n^E & 0 & I_n\gamma_{USn}^E & (1-I_n)\gamma_{EUn}^E & 0 & \cdots & \phi_n^E & 0 & \cdots & 0 \\ \lambda_1^B & 0 & \delta_1^B & I_1\gamma_{US1}^B & (1-I_1)\gamma_{EU1}^B & 0 & \cdots & 0 & \phi_1^B & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \lambda_n^B & 0 & \delta_n^B & I_n\gamma_{USn}^B & (1-I_n)\gamma_{EUn}^B & 0 & \cdots & 0 & 0 & \cdots & \phi_n^B \end{bmatrix} \begin{bmatrix} C \\ M^E \\ M^B \\ R^{US} \\ R^{EU} \\ f_1^E \\ \vdots \\ f_n^E \\ f_1^B \\ \vdots \\ f_n^B \end{bmatrix}$$

(4.28)

In compact matrix notation (4.27) is written as:

$$r^{**} = \mathrm{B}F \qquad (4.29)$$

The decomposition is the same as those describe for equation (4.24), namely,

$\dfrac{\lambda_i^2}{\mathrm{var}(r_i^{**})}$ = the contribution of the common (bond and stock) factor to the variance of the residual equity and bond returns.

$\dfrac{\delta_i^2}{\mathrm{var}(r_i^{**})}$ = the contribution of the asset market factor to the variance of the residual equity and bond returns.

$\dfrac{\gamma_i^2}{\mathrm{var}(r_i^{**})}$ = the contribution of the regional factor to the variance of the residual equity and bond returns.

$\dfrac{\phi_i^2}{\mathrm{var}(r_i^{**})}$ = the contribution of the idiosyncratic factor to the variance of the residual equity and bond returns.

4.23 Tests for capital market integration

To test for capital market integration we examine the size of the contribution of the idiosyncratic factor to the overall variance. The larger the residual contribution the more segmented the asset market is. In other words, idiosyncratic factors are more important in segmented asset markets. A further robustness test of market segmentation is to extract the various factors and examine the variance-covariance and correlation matrices of the idiosyncratic factors. Statistical tests of significance for elements (individual bilateral correlations) of the correlation matrix would determine whether the factors are truly idiosyncratic. We describe this test shortly. The unobserved idiosyncratic factors in the model can be extracted once estimated by applying the Kalman filter to the system. The Kalman filter is a recursive procedure that computes the unobserved variables using some initial information. Extensive discussions of the Kalman filter including empirical applications can be found in for example, Diebold (1989), Cuthbertson, et al. (1992), Harvey (1993), Lutkepohl (1993), Hamilton (1994a, b), Harvey, et al. (1995), Wells (1996), Koopman, et al. (1999), Kim and Nelson (1999), Harvey and Koopman (2000) and Chan (2002). To apply the Kalman filter, we write the model in the following general state-space form and estimate by Gaussian maximum likelihood[195]:

$$F_t = A_t F_{t-1} + w_t \qquad \textbf{Transition equation} \qquad (4.30)$$

$$r_t^* = \beta' F_t + v_t \qquad \textbf{Measurement equation} \qquad (4.31)$$

r_t^* is an n-dimensional vector of underlying, zero mean, variables (the filtered of residual equity returns series or benchmark long-term government bond returns) observed at time t. F_t is an m-dimensional vector of unobserved variables at time t and, w_t and v_t are multivariate white noise residuals. The idea here is to estimate the dynamics of the latent factors, F_t, and the factor loading A_t. Equation (4.30) defines the path of the unobserved vector of states or unobserved factors, F in equation (4.25), and equation (4.31) gives the return generating process of the residual equity or benchmark long-term government returns. The aim of the Kalman filter is to extract information about latent factors from the observed returns. The general state-space representation is equivalent to a dynamic factor model (See for example, Stock and Watson (1989) and Kapetanios and Marcellino (2003)). Due to the various restrictions imposed on the original factor model, the formulation used here is equivalent to a restricted dynamic factor model. We extract the unobserved individual idiosyncratic equity return factor and the unobserved individual idiosyncratic bond return factor. Extraction of the factors in the joint model (equation (5.28)) is left for future work.

As further robustness test of capital market segmentation, we construct a correlation matrix of the extracted unobserved idiosyncratic residuals and test for the independence of this matrix – all bilateral correlations are equal to zero. We use a generalised likelihood ratio test. Lawley (1940) and Bartlett (1954) have both provided an asymptotic chi-squared statistic that approximates the limiting distribution of this test. We opt for Lawley's test. The null hypothesis in Lawley's asymptotic tests (see Mudholkar, et al. (1982), Muirhead (1982) and Morrison (1990)) is that the correlation matrix is diagonal (an identity matrix): $H_0 : P = I$; the alternative hypothesis is that at least one bilateral correlation is not equal to

[195] We provide a brief discussion of the Kalman filter in Appendix 2.

zero: $H_1 : P \neq I$. The test is based on the following asymptotic chi-squared statistic:

$$\chi^2 = \left(N - 1 - \frac{2p+5}{6} \right) \sum_{i<j}\sum r_{ij}^2 \qquad (4.32)$$

N is the number of observations; p is the dimension of the correlation matrix and; $\sum_{i<j}\sum r_{ij}^2$ is the sum of squared unique elements of the correlation matrix – the bilateral correlations. The generalised likelihood ratio statistic approximated in (4.32) is equal to -2 times the $1/2Nth$ power of the log-determinant of the correlation matrix: $-2\left(\ln|R|^{\frac{N}{2}} \right)$; where R is the correlation matrix[196]; see Mudholkar, et al. (1982) and Morrison (1990). Lawley's statistic has $p(p-1)/2$ degrees of freedom. The decision criterion is: if $\chi^2 < \chi^2_{\alpha;1/2p(p-1)}$, accept the null hypothesis; reject if otherwise.

The bilateral correlation coefficients (elements of the correlation matrix) are also tested individually to see which correlations are significant because Lawley's test would reject the independence of the entire correlation matrix if at least one of the bilateral correlations were different from zero. The significance of the individual bilateral correlations is tested asymptotically using Fisher's z-transform (see Morrison (1990), page 104) of the standard t-test of the significance of bilateral correlations, $t = r\sqrt{\frac{N-2}{1-r^2}}$; which has an N-2 degrees of freedom, where N is the number of observations and r the correlation coefficient. We report the Bonferroni-

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[196] Bartlett (1954) (see Anderson (1984) and Morrison (1990)) suggests using the log-determinant of the correlation matrix, $\ln|R|$, in place of $\sum_{i<j}\sum r_{ij}^2$ in Lawley's statistic and multiply the entire expression by -1.

adjusted p-value for the critical absolute correlation coefficient. This critical value is the critical multiple-comparisons magnitude for testing individual correlation coefficients (Morrison (1990))[197]. This test would allow us to get a clearer picture of the overall significance of the individual bilateral correlations[198]. It would be used to assess the extent of residual interdependence or unobserved residual capital market integration in the G10 capital markets. Specifically, it would allow us to isolate the truly idiosyncratic markets. Those markets with insignificant correlations could be regarded as segmented or at least having a spurious relationship with a particular market in terms of the residual unobserved idiosyncratic returns. We will also look at the average correlations across the markets. The average correlation is very important from a macroprudential point of view especially for regulatory authorities monitoring international financial stability (Borio (2003)).

4.3 Data and Preliminary Econometric Analysis

4.31 Data Description

The data consists of equity and long-term government bond data from the G10 group of countries. The G10 group of countries based on the International Monetary Fund (IMF) classification are: Canada, US, Belgium, France, Germany, Italy, Netherlands, Switzerland, Sweden, UK and Japan. For equity markets, we use the Datastream™ calculated value weighted equity market index. For bond markets, we use the long-term (10 years or more) benchmark government bond index obtained from Datastream™. The data are in weekly frequency and we use

[197]For the Bonferroni-adjusted p-value, the observed significance level is adjusted for the fact that multiple comparisons are being made, Rice (1995). Chapter three of Morrison (1990) discuses these tests in greater detail.

[198] Routines for carrying out this test are available in the excellent multivariate statistical analysis library for Matlab™ provided by Richard E. Strauss of Texas Tech University.

the total return index[199], which accounts for capital gains. Weekly data are less noisy and accounts for non-synchronous trading effects across the G10 markets. Summary statistics of both returns series are given in Table 4.1 and Table 4.2.

Table 4.1: Summary statistics for G10 and world equity return series from January 1982 – August 2003

	CAN	US	BEL	FRA	GER	ITA
Min:	-0.1651	-0.1439	-0.1023	-0.1504	-0.1121	-0.2061
Mean:	0.0020	0.0025	0.0026	0.0027	0.0020	0.0019
Max:	0.0973	0.0895	0.1128	0.1052	0.1093	0.1733
Variance:	0.0005	0.0005	0.0006	0.0007	0.0007	0.0011
Std Dev.:	0.0229	0.0223	0.0236	0.0266	0.0267	0.0328
SE Mean:	0.0007	0.0007	0.0007	0.0008	0.0008	0.0010
LCL Mean*:	0.0006	0.0012	0.0012	0.0011	0.0005	-0.0001
UCL Mean:**	0.0033	0.0038	0.0040	0.0042	0.0036	0.0038
Skewness:	-0.5334	-0.6265	-0.1889	-0.3368	-0.2778	-0.1128
Kurtosis:	4.8326	4.3006	1.6084	1.9831	1.5390	2.9013
	NETH	**SWIT**	**SWED**	**UK**	**JAP**	**WOR**
Min:	-0.1228	-0.1657	-0.1686	-0.2234	-0.1310	-0.1361
Mean:	0.0028	0.0025	0.0024	0.0024	0.0013	0.0021
Max:	0.1364	0.1133	0.2169	0.1082	0.1166	0.0771
Variance:	0.0006	0.0006	0.0011	0.0006	0.0010	0.0004
Std Dev.:	0.0235	0.0239	0.0337	0.0247	0.0310	0.0193
SE Mean:	0.0007	0.0007	0.0010	0.0007	0.0009	0.0006
LCL Mean*:	0.0014	0.0011	0.0005	0.0009	-0.0005	0.0010
UCL Mean:**	0.0042	0.0039	0.0044	0.0038	0.0031	0.0033
Skewness:	-0.4826	-0.3679	-0.2493	-0.5946	0.1094	-0.4933
Kurtosis:	3.0117	3.3478	3.0795	6.6449	1.3971	3.9870

**LCL implies the lower confidence limits of the mean and; **ULC implies the upper confidence limits of the mean.*

The equity indices are from 8 January 1982 to 8 August 2003. The bond indices are from 29 March 1991 to 8 August 2003. We compute the continuously compounded returns as the natural logarithms of the price changes: $ln(P_t / P_{t-1})$. This produces 1,126 observations for equity returns and 645 observations for bond returns. The joint dataset has 645 observations. All the level price data contained a unit root and but the continuously compounded returns were found to be stationary[200]. The distributional properties of equity and government bond returns could be assessed

[199] The total return index is basically a price data that has been adjusted for dividends or other capital gains.
[200] This finding is consistent with evidence reported in chapter 4.

from the descriptive statistics reported in Tables 4.1 and 4.2. For equity returns (Table 4.1), all the G10 markets offer positive mean returns and with all of them being significant as they all fall between their respective lower and upper confidence limits. The equity markets also appear to be relatively risky as measured by the variance or standardised variance (the standard deviation). Italy, Sweden and Japan were the most risky markets with standard deviation exceeding 300 basis points or 3%[201]. We assess the shape and overall patterns of the distribution of returns by looking at the measures of skewness and kurtosis. Skewness measures the degree of symmetry and kurtosis measures the degree of peakedness. All of the equity markets, with exception of Japan, are slightly negatively skewed with values ranging from -0.11 to -0.59. Ideally, for the distribution to be symmetrical or normal, skewness should be very close to zero.

Table 4.2: Summary statistics for G10 benchmark long-term benchmark government bond return series from January 1991 – August 2003

	CANGB	USGB	BELGB	FRAGB	GERGB	NETHGB
Min:	-0.0441	-0.0434	-0.0400	-0.0464	-0.0512	-0.0464
Mean:	0.0014	0.0014	0.0017	0.0017	0.0015	0.0016
Max:	0.0481	0.0270	0.0564	0.0515	0.0588	0.0584
Variance:	0.0002	0.0001	0.0003	0.0003	0.0003	0.0003
Std Dev.:	0.0134	0.0100	0.0162	0.0164	0.0165	0.0164
SE Mean:	0.0005	0.0004	0.0006	0.0006	0.0006	0.0006
LCL Mean*:	0.0004	0.0006	0.0005	0.0004	0.0002	0.0003
UCL Mean**:	0.0025	0.0022	0.0030	0.0030	0.0028	0.0029
Skewness:	-0.1434	-0.5683	0.1586	0.0807	0.1352	0.1056
Kurtosis:	0.5157	0.8200	0.1471	0.0118	0.3526	0.2666
	ITAGB	**SWEDGB**	**SWITGB**	**UKGB**	**JAPGB**	
Min:	-0.1093	-0.0886	-0.0600	-0.0831	-0.0595	
Mean:	0.0018	0.0016	0.0014	0.0017	0.0016	
Max:	0.0710	0.0640	0.0608	0.0619	0.1314	
Variance:	0.0004	0.0004	0.0003	0.0002	0.0003	
Std Dev.:	0.0189	0.0196	0.0172	0.0155	0.0176	
SE Mean:	0.0007	0.0008	0.0007	0.0006	0.0007	
LCL Mean*:	0.0004	0.0001	0.0001	0.0005	0.0002	
UCL Mean**:	0.0033	0.0032	0.0027	0.0029	0.0029	
Skewness:	-0.3643	-0.2804	0.1123	-0.3449	0.9004	
Kurtosis:	2.1311	1.0409	0.4550	1.5287	5.3308	

**LCL implies the lower confidence limits of the mean and; **ULC implies the upper confidence limits of the mean.*

[201] 1 basis point is equivalent to 0.001% - that is 1% of 1%.

High Kurtosis value is reported for all equity markets which imply that there is a high peak at the centre of the data. In general, the summary statistics confirms stylised facts about equity returns: equity markets are very risky and the distribution of returns is very close to the normal distribution but not perfectly normal.

For government bond markets (Table 4.2), all of the markets also offered positive mean returns and were all significant with their given confidence bounds. The government bond markets appear to be less risky compared to the equity markets. The standard deviations across the bond markets were relatively smaller; all under 200 basis point or 2%. Skewness and kurtosis measures also suggest that distribution of government bond returns were closer to be normally distributed than the equity markets. All skewness measures, except for Japan, were all with 0.5 decimal point of zero. Kurtosis values were not as high as in the equity markets; ranging from 0.01 to 5.33. Large values of kurtosis usually imply a high peak at the centre of the data, and small values imply a broad peak at the centre. For perfect normality kurtosis is equal to 3.

4.32 Correlation Analysis

The Correlation coefficient between two capital markets is regarded as a first pass test or a crude measure of capital market integration[202]. If capital markets are integrated, it normally expected that the correlation between these markets would be very high. The correlation matrix for asset returns is also very useful for a wide rage of market participants. For example, regulatory bodies such as financial services authorities or central banks would utilise this information for financial stability monitoring purposes. It could be used to gauge the extent of absolute movements in a particular market due to shocks emanating from another market. Portfolio managers and institutional investors would also use this information in devising international asset allocation strategies.

Figure 4.1 summarises the correlations between the various markets based on equity returns (above the leading diagonal) and long-term benchmark bond returns (below the leading diagonal). The Red and brown shading denote very high (>0.6) and high (0.5-0.6) correlations respectively, while yellow and blue denote low (0.4-0.5) and very low (<0.4) correlations respectively. The preponderance of red in the bottom-left quadrant implies generally high correlation between European government bond markets especially for Belgium, France, Germany and Italy. Similarly, European equity markets show some strong links, the top-left quadrant. The Japanese bond market and equity appear to be the most segmented market with correlations of 0.4 or below in all cases. The mixture of colours for the US government bond market correlations implied the US government bond market is typically less highly correlated with the other G10 government bond markets. The hot and cold spots in the four quadrants give a general idea of the correlations of between the individual asset markets in the G10 countries.

These hot and clod spots could be viewed as the extent of unconditional capital market integration between the G10 markets countries. There are more hot spots in the bond market correlations segment than in the equity market correlations segment suggesting perhaps that G10 government bond markets, especially for the core European countries are more integrated or interrelated than the G10 equity

[202] In fact, most of the early studies of capital market integration conducted hypothesis that were

markets. This initial finding should however be interpreted with caution due potential structural problems with unconditional correlation estimates. Unconditional correlation estimates have been questioned because of the equal weights assigned to observations when correlations are computed. Secondly, the correlation matrices of assets returns might not be stable over time due to a number of reasons; which we discuss in the next sub-section when we investigate the stability of correlation and covariance matrices. Relying solely on surface (aggregate) level correlation estimates could therefore be problematic. The ideas developed in this chapter goes beyond the surface (aggregate) level correlations and decompose the variance contributions so as to determine the factors driving these correlations.

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almost exclusively based on simple correlation estimates. See for example Levy and Sarnat (1970).

Figure 4.1 Correlation Matrices: Heatmap of Bivariate Correlations Using Equity Returns and Benchmark Long-term Bond Returns

	CAN	US	BEL	FRA	GER	ITA	NETH	SWED	SWIT	UK	JAP
CAN	-	0.71	0.33	0.47	0.42	0.30	0.54	0.45	0.42	0.50	0.28
US	0.56	-	0.32	0.46	0.45	0.32	0.55	0.43	0.41	0.49	0.25
BEL	0.25	0.38	-	0.60	0.63	0.44	0.67	0.43	0.64	0.52	0.32
FRA	0.26	0.41	0.93	-	0.68	0.52	0.68	0.53	0.63	0.57	0.37
GER	0.23	0.39	0.95	0.92	-	0.54	0.75	0.59	0.71	0.56	0.37
ITA	0.27	0.43	0.95	0.93	0.98	-	0.51	0.45	0.47	0.44	0.26
NETH	0.32	0.35	0.69	0.73	0.68	0.68	-	0.53	0.72	0.69	0.38
SWED	0.31	0.31	0.66	0.66	0.62	0.65	0.68	-	0.53	0.46	0.31
SWIT	0.14	0.30	0.84	0.81	0.86	0.86	0.55	0.51	-	0.59	0.40
UK	0.36	0.47	0.67	0.68	0.65	0.67	0.58	0.55	0.55	-	0.35
JAP	0.09	0.08	0.36	0.35	0.38	0.37	0.20	0.17	0.39	0.19	-

Key: Correlations of equity returns are given above the leading diagonal, correlations of benchmark long-term government bond returns are given below the leading diagonal. To read the correlations: For the lower part, read across and down and for the upper part read down and across.

Correlation:

- Greater than 0.6
- Between 0.5 and 0.6
- Between 0.4 and 0.5
- Less than 0.4

4.3.3 Testing the stability of correlation and covariance matrices of G10 equity and bond markets

The basic factor modelling technique assumes that correlation and covariance matrices are stable. However, the review of the empirical literature suggests that financial asset prices are best described by time-varying risk characteristics. Correlations could therefore be time-varying. The empirical evidence also suggests that correlations between capital markets are at their highest levels during markets downturns or periods of instability. There could be several reasons why correlations breakdown. For example, it could be the results of structural break in the data (distribution of returns) or contagion across markets (Boyer, et al. (1997), Forbes and Rigobon (2002)), the existence of large extreme returns in the tails of the distribution (Longin and Solnik (1995)) or the occurrence of the so-called low probability and high impact events that affects markets (Loretan and English (2000a)).

To test whether the above correlation matrix is stable over time, we outline a formal test for the stability of correlation and covariance matrices. The tests described here, are multivariate generalisations of standard F-tests for changes in variances or T-tests for changes in average correlations. They were suggested by Jennrich (1970). Kaplanis (1988) and Longin and Solnik (1995) have applied this test to equity markets correlations and covariances. Jennrich proposed the following statistic to test the stability of two correlation matrices:

$$\chi^2 = \frac{1}{2}tr(Z^2) - diag'(Z)S^{-1}diag(Z) \qquad \textbf{(4.33)}$$

$$Z = c^{1/2} R^{-1} (R_1 - R_2); \quad R = (n_1 R_1 + n_2 R_2)/(n_1 + n_2); \quad c = n_1 n_2 /(n_1 + n_2)$$

R_1 and R_2 are the two sample correlation matrices; n_1 and n_2 are the numbers of observations in the original data series.

$S = (\delta_{ij} + r_{ij} r^{ij})$; δ_{ij} is the kroneker delta (the identity matrix)[203]; r_{ij} and r^{ij} are respectively the elements of R and R^{-1} (the inverse of R). The statistic tests the null hypothesis that the two correlation matrices are stable (equal) against the alternative hypothesis that correlation matrices are not stable (equal). It has an asymptotic Chi-square (χ^2) distribution with $p(p-1)/2$ degrees of freedom (p being the dimension of the correlation matrix).

The test for the stability of the stability of two covariances matrices is deduced from the statistic for comparing two correlation matrices. If the two sample correlation matrices are replaced by the sample covariances, the statistic for the stability of covariance matrices now becomes:

$$\chi^2 = \frac{1}{2} tr(Z^2) \qquad \textbf{(4.34)}$$

with $p(p+1)/2$ degrees of freedom[204]. There are other methods for testing the stability of covariances matrices but, to our knowledge these have not been

[203] A matrix with ones on the principal diagonal
[204] All other terms remain as previously defined

applied to financial markets. The modified likelihood ratio test is an example[205]. The test is described in the appendix to this chapter.

Table4.1 and chart4.1 gives the results for the Jennrich test for the stability of the correlation and covariance structure of weekly US dollar denominated G10 equity market returns between 1982 and 2003. The tests are asymptotically distributed chi-square with 55 degrees of freedom for the correlations matrices and 66 degrees of freedom for the covariance matrices. The results indicate a highly unstable correlation and covariance matrices for both the overlapping and the non-overlapping sub-samples. Overlapping sub-samples are for example, comparing a given sample to its subset. Panel A are for overlapping sub- sample periods and Panel B for non-overlapping sub-samples.

Similar results were obtained for the bond market data although there were fewer numbers of observations. We note that the power of statistical tests of this nature might be subject to questions. The results however justify our suggested approach of rewriting the restricted latent factor model in dynamic form and estimate by Kalman filter before extracting the factors. This method is robust to time-variation in the data. In subsequent sections we apply techniques that summarise the key features of the correlation and covariance matrices of G10 markets asset prices to fully understand the common factors that drive the asset

[205] The test is based on Bartlett's modification of the likelihood ratio statistic for the equality of covariance matrices. For a theoretical background and some proofs, see Perlman (1980), Anderson (1984) or Morrison (1990)

prices and to identify the extent of the heterogeneity of the equity and bond markets in G10 countries.

Table 4.2a: Test of the equality of correlation and covariance matrices over time[(a)(b)(c)]

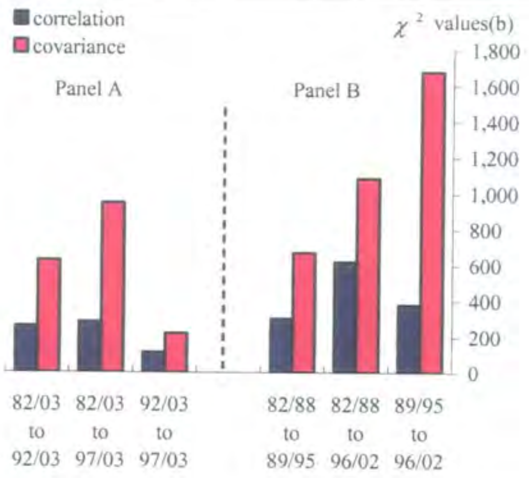
Time periods campared	Correlation matrix Test	Correlation matrix p-value	Covariance matrix Test	Covariance matrix p-value
Panel A				
1982/03 to 1992/03	261.397	0.000	629.963	0.000
1982/03 to 1997/03	285.010	0.000	948.559	0.000
1992/03 to 1997/03	114.690	0.000	222.455	0.000
Panel B				
1982/88 to 1989/95	303.188	0.000	670.600	0.000
1982/88 to 1996/02	620.682	0.000	1086.361	0.000
1989/95 to 1996/02	379.741	0.000	1679.167	0.000

a) The null hypothesis is that the correlation and covariance matrices are stable over time

b) The column labelled test contain Chi-squared calculated values which are based on equation 5.1 for correlations and equation 5.2 for covariances.

c) The column labelled p-value gives the probability of failing to reject the null hypotheses.

Figure 4.2: Chi-square calculated values for weekly G10 correlation and covariance matrices[(a)(c)]



a) The null hypothesis is that the correlation and covariance matrices are stable over time.

b) Chi-squared calculated values are based on equation 5.1 for correlations and equation 5.2 for covariances.

c) All chi-squared calculated values are above the 5% critical values for 55 and 66 degrees of freedom therefore rejecting the null hypotheses.

4.3.4 Cluster Analysis

Cluster analysis attempts to determine the natural grouping of observations and is best viewed as an exploratory data analysis technique. It searches for groups or clusters in the data and generally identifies two classes of variables – similar and dissimilar. Variables that are similar belong to the same cluster and variables that are dissimilar are in different clusters. It is applied here to determine groups of G10 countries whose equity or benchmark government returns behave in similar ways. Anecdotal evidence of increased globalisation of G10 capital markets suggests that G10 capital markets are probably driven by common factors. The factors could be proxies of commonality across economic fundamentals in these countries. The number and nature of these common factors are discussed in later sections.

There are many types of cluster analysis method or algorithms[206]. In this chapter we use one of the most popular – agglomerative hierarchical cluster analysis. The algorithm begins with each observation (G10 equity or benchmark government bond returns) being viewed as a separate group (giving *N* groups each of size 1). The closest two groups are then combined (giving *N*-2 groups of 1, and one group of 2). This process continues until all observations are combined into one group (of *N* equity or benchmark government bond returns).

The agglomerative technique of cluster analysis involves at least two choices at the outset of the analysis – which dissimilarity measure is to be used to compare observations and what should be compared when groups contain more than one country. The first choice is relatively straightforward. Since we have time series

[206] Kaufman and Rousseeuw (1990) give an extended overview of these methods.

of normalised stock returns for each observation, the Minkowski distance metric with argument 2, the default metric in most cluster analysis packages, forms the same clusters as would occur when comparing correlations.[207] Limited experimentation suggests that the results are robust to the use of other dissimilarity measures.

The decision of how to compare correlations when groups contain more than one market is less straightforward. One method is to compute the dissimilarity between two groups as the dissimilarity between the closest pair of observations between the two groups (known as single linkage or nearest neighbour clustering). At the other end of the spectrum, complete linkage or furthest neighbour clustering uses the farthest pair of observations in the two groups to determine dissimilarity. The middle route of average linkage clustering, not surprisingly, uses the average dissimilarity of observations between groups. Single linkage clustering tends to produce long, thin clusters and is not used below. The other two methods typically produce more compact groupings that are amenable to the type of analysis we wish to perform. Here we use the average method based on arguments of robustness and consistency but again our main findings seem robust to using complete linkage clustering. We report the furthest neighbour cluster analysis results in appendix x[208].

The clustering results of the G10 equity returns are shown in Figure 5.3. We identify an emerging cluster of European capital markets. The cluster begins a Netherlands-Switzerland block and they are joined by Germany, Belgium and

[207] The Minkowski distance metric with argument 2 computes $\sqrt{\sum_{t=1}^{T}\left(x_{ti}-x_{tj}\right)^{2}}$ where x_{ti} denotes the equity return (or benchmark government bond return) for G10 market i at time k.

France and the UK in close succession. A US-Canada block which is identifiable from the start joins this emerging European block to form a US-Europe block. Sweden, Italy and Japan appear to be segmented (an outlier) from this group, joining the group very late to complete the clustering tree. The late joining of Sweden, Italy and Japan, measured by the distance between the start of the dendrogram and when they joined the group, indicate a high level of idiosyncrasies in these markets. This reflects the less than perfect correlations reported for these three countries reported in the correlation matrix, especially for Japan.

The clustering of G10 benchmark long-term government bond returns (Figure 4.4) reveals a different picture. The only identifiable group at the start of the clustering tree is the German and Dutch government bond markets. This group is joined in quick succession by the Belgian and French government bond market. The early clustering of these markets reflects the substantially high bilateral correlations reported for them. The remaining G10 government bond markets appear to be very far away from this mainly European group. Switzerland and UK were next to join the group followed by an evenly spaced addition of Italy, Sweden and the US-Canada sub-group.

The US-Canada sub-group appears to have formed at the half-way point of the dendrogram. Although this is further than in the case of the equity markets, this formation of the US-Canada sub-group seems to be consistent in the government bond market. This grouping perhaps reflects close financial and economic linkages between US and Canada.

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[208] Further details on cluster analysis can be found in Kaufman and Rousseeuw (1990).

The most consistent result from the clustering analysis is the Japanese capital market. Similar to the equity return clustering tree, the Japanese government bond market is the most idiosyncratic or segmented bond market. It was the last to join the dendrogram. The correlation matrix reveals a very similar picture. The average bilateral correlations between Japan and the other G10 capital market is the lowest within the group. Japan bilateral equity return correlation is 0.26 and the bilateral government bond correlation is 0.33.

Cluster analysis is not an exact science and robustness testing is important. One consideration is that the correlations and clusters calculated previously may be merely picking up the fact that a number of the G10 equity were highly correlated with world stock market index rather than with each other. We also hypothesise that the outlying behaviour of some markets especially Japan were driven by substantial market segmentation. The factors driving market segmentation are unobservable. To concentrate on the true correlation between the national markets, we filter out the world stock market effects by performing the following regression for equity returns[209]:

$$r_t = \alpha + \beta W_t + r_t^* \qquad \textbf{(4.35)}$$

where the dependent variable is the equity return for a G10 equity market at time t, W represents the return on the world equity index. Cluster analysis is then performed on the residuals of the regression, r^*, which are free from world

[209] As noted earlier, it was not possible to perform a similar filtration for government bond market due to the lack of a good world bond market index for benchmark long-term government bonds.

market effects. The resulting dendrogram (Figure4. 4) shares many of the same attributes as in raw equity returns case. The US-Canada and the emerging European block were clearly identifiable. Sweden, Italy and Japan remain outliers with being the most segmented market.

Figure 4.3: Dendrogram using Average linkage (between groups) clustering for G10 Markets Equity Returns

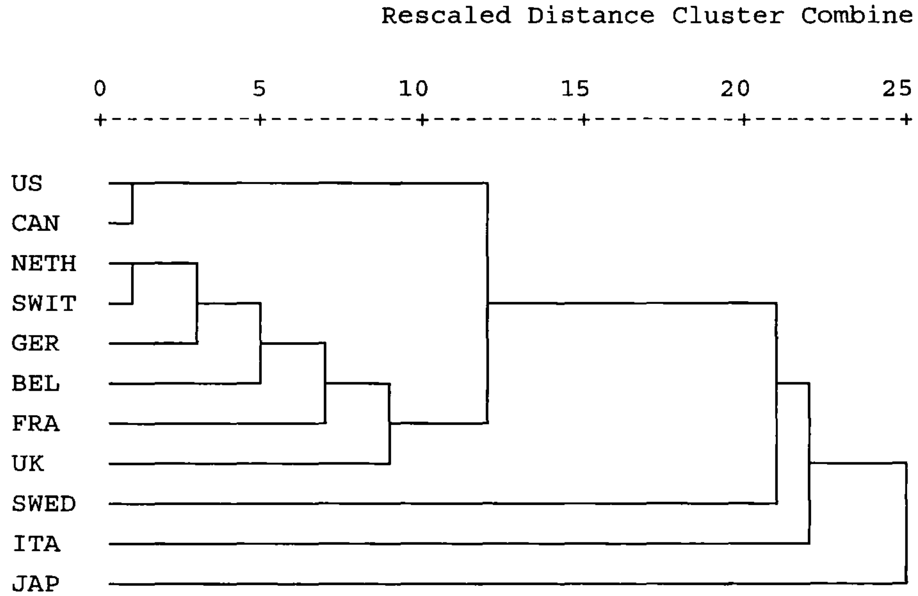


Figure 4.4: Dendrogram using Average linkage (between groups) clustering for G10 Markets Benchmark Government Bond Returns

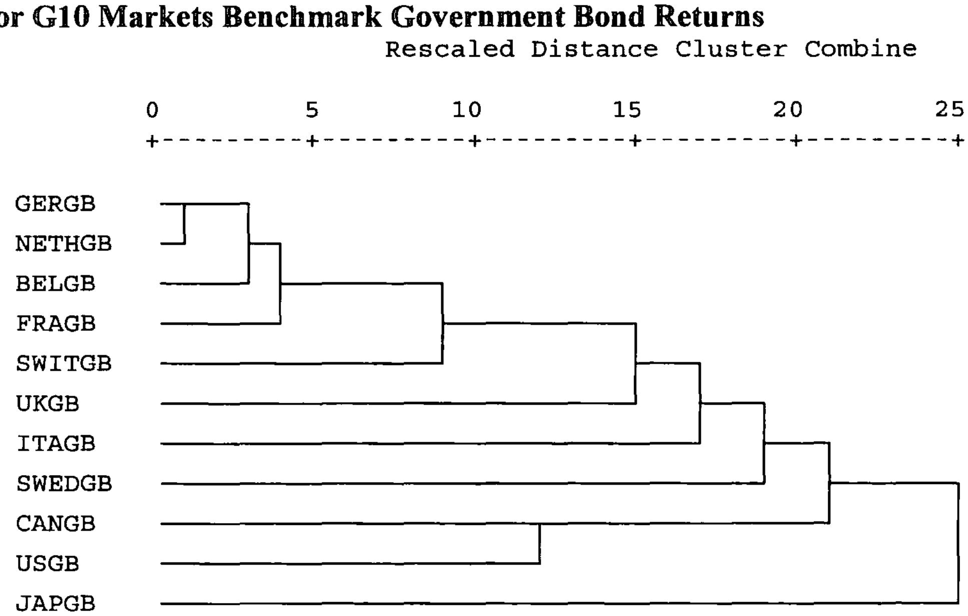
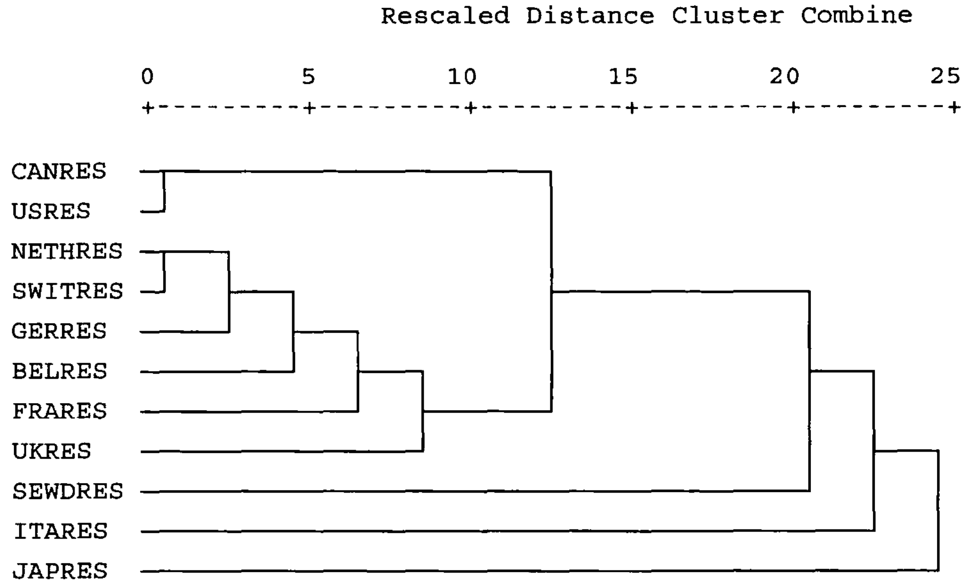


Figure 4.5: Dendrogram using Average linkage (between groups) clustering for G10 Markets residual (filtered) equity returns



4.3.5 Principal Component Analysis (PCA)

The return generating process of financial asset prices are normally determined from asset pricing models. The well-known and widely used Capital Asset Pricing Model (CAPM) suggests that the risk premium earned on equity is the product of the risk premium on the market portfolio and the beta of the individual security. The CAPM is a single factor model, where the factor is the market risk premium and the loading on that factor equals the security's beta. However, more general models of asset prices, such as the Arbitrage Pricing Theory (APT), suggest that multiple factor models should be more appropriate. Unfortunately, these more general models typically do not specify what those factors are and even how many factors are needed to price assets. As noted earlier, some approaches pre-specify macroeconomic variables, Chen, et al. (1986), proxies for fundamental variables Fama and French (1993). Others extract the unspecified factors using a statistical approach such as factor analysis, Roll and Ross (1980), maximum explanatory component analysis, Xu (2003) or principal components analysis (Connor and Korajczyk, 1986,1988, 1993).

Principle component analysis is a dimension reduction technique applied to the correlation or covariance matrix of returns to determine the most important uncorrelated sources of variation in asset returns. The idea is to reduce the dimension of the data without loosing information provided by the covariance between the original variables. For N assets, there are N principal components and these are just linear combinations of the returns. For identification, the number of observations should be greater than the number of assets[210]. The principal components are constructed and ranked so that the first principal component of the observations explains the largest portion of the sample covariance or correlation matrix of returns, the next principal component the next largest and so on. In this section we use the correlation matrix which is equivalent to using a standardised linear combination of the variables (returns)[211].

In this section, and as a precursor to the factor modelling performed in the following section, we apply principal components analysis to our asset prices. The objective is to determine how many factors are needed to adequately explain the return generating process of G10 equity and long-term government bond

[210] Connor and Korajczyk (1986) suggested using asymptotic principal component analysis when the cross-section of assets is greater than the number of observations.

[211] In the academic literature, see for example Mardia, et al. (1979), Anderson (1984) and Morrison (1990), the general assumption is that correlation matrices are more stable than the covariance matrices. For G10 equity and bond markets, our own analysis (Table 4.2 and Figure 4.2) suggests that that both the correlation and covariance matrices were highly unstable although the covariance matrix does appear to be the most unstable. The other advantage of using correlation matrix is that the principal component (factor) loadings are not affected by the differences in the variances of the original variables.

returns. Further, consideration of the factor loadings may give insights into the nature of the factors[212].

Most principal components studies in financial economics select a cut-off number in the range 0.8-1.0. If the eigenvalue for a component falls below this cut-off number, the factor is not considered significant in explaining returns. The second panel of Table 4.3 suggests that either two or three components are significant for equity returns depending on the exact cut-off number selected. The first two components explain over sixty percent of the variance in returns, the third component explains a further seven percent, and the fourth component explains almost six percent.[213] The third panel of Table 4.3 gives the eigenvectors associated with the first seven eigenvalues[214]. These eigenvalues are the principle component or factor loadings. The first component appears to be common to all G10 equity markets since the eigenvectors are of similar magnitude and all positive.

The second component discriminates between US-Canada and European countries although; the UK and Switzerland have the same sign as US and Canada, suggesting perhaps that in directional terms the UK and Switzerland can join the US-Canada factor. The marginal third component seemed to give mixed results and is difficult to interpret. It appears to be capturing the idiosyncrasies in

[212] We also use the principal component loadings as starting values in the GMM estimation of the restricted latent factor models in the next section.

[213] Since we are trying to model individual stock returns, the cumulative proportion explained is likely to be relatively low compared to studies that use portfolio returns where idiosyncratic risk is diversified away.

[214] The eigenvectors are needed because they provide us with the linear combination of the variables –the principal components – that contribute to the variance. The eigenvalues are required since they describe the proportion of total risk accounted for by each principal component.

the Japanese market (0.94 factor loading) and number of other mainly European and the US markets have identical sign

Table 4.3: Principal Component Analysis of G10 Equity Returns

	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5	Comp 6	Comp 7
Eigenvalue	6.01	1.07	0.78	0.65	0.54	0.45	0.36
Variance Prop.	54.67%	9.74%	7.13%	5.91%	4.94%	4.06%	3.30%
Cumulative Prop.	54.67%	64.41%	71.54%	77.45%	82.38%	86.44%	89.74%
Eigenvectors:	**Vector 1**	**Vector 2**	**Vector 3**	**Vector 4**	**Vector 5**	**Vector 6**	**Vector 7**
Variable							
CAN	0.26875	-0.6094	0.029976	-0.00519	-0.03487	-0.14627	0.15196
US	0.268324	-0.60628	-0.02944	-0.01629	-0.09241	-0.23478	-0.00323
BEL	0.302123	0.317805	-0.09593	-0.38068	0.040279	-0.318	0.690242
FRA	0.333087	0.105799	-0.07072	-0.00742	-0.03972	-0.25895	-0.52506
GER	0.343834	0.187989	-0.10277	0.007076	0.191988	-0.14499	-0.33803
ITA	0.264078	0.223156	-0.25187	0.639255	-0.59542	-0.06409	0.156306
NETH	0.359758	0.030484	-0.06628	-0.24101	-0.04197	0.05155	-0.05091
SWED	0.287588	-0.04182	-0.07527	0.515389	0.691623	0.272518	0.218889
SWIT	0.335028	0.207589	0.011726	-0.19658	0.154545	0.043672	-0.18108
UK	0.314321	-0.06628	0.001348	-0.24237	-0.28985	0.804577	0.02466
JAP	0.205955	0.116425	0.948597	0.157934	-0.0875	-0.06331	0.046655

Analysis of the residuals, r^*, of equation (4.33) suggest that as many as five principal components may be significant (Table 4.5). The interpretation of the first two appears to have remained the same – the first component is common to all G10 equity markets and the second differentiates between US-Canada and European markets. The first component is interpreted as common because most the loadings are of similar size and have the same sign. This implies that even when purged of local and world market effects, important common and regional factors remain. The other components are less easily interpreted but their significance suggests that there is structure beyond the simple common and regional effects already noted.

Table 4.4: Principal Component Analysis of G10 Residual (Filtered) Equity Returns

	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5	Comp 6	Comp 7
Eigenvalue	3.40	2.00	1.00	0.83	0.82	0.70	0.61
Variance Prop.	30.90%	18.16%	9.08%	7.53%	7.46%	6.40%	5.56%
Cumulative Prop.	30.90%	49.06%	58.14%	65.67%	73.13%	79.53%	85.09%
Eigenvectors:	**Vector 1**	**Vector 2**	**Vector 3**	**Vector 4**	**Vector 5**	**Vector 6**	**Vector 7**
Variable							
CANRES	-0.00726	0.471523	0.003072	-0.20588	-0.44673	0.629427	-0.3221
USRES	0.137236	0.608504	0.023986	-0.05944	0.29814	-0.15925	0.057675
BELRES	-0.37517	-0.08042	-0.19869	-0.21791	0.232319	0.082994	-0.01881
FRARES	-0.36142	0.016364	0.097291	-0.01221	0.148599	0.502308	0.716997
GERRES	-0.41122	-0.02842	0.167843	-0.20465	0.163889	-0.17225	-0.07482
ITARES	-0.27304	-0.03206	0.415549	0.682615	0.23301	0.231208	-0.39763
NETHRES	-0.40779	0.093455	-0.27704	-0.10232	0.033527	-0.05227	-0.19633
SEWDRES	-0.24204	0.075451	0.633771	-0.12666	-0.52741	-0.34182	0.173974
SWITRES	-0.39317	-0.07929	-0.11317	-0.27445	-0.03693	-0.1188	-0.32018
UKRES	-0.26561	0.084163	-0.5083	0.526578	-0.47658	-0.17598	0.189776
JAPRES	0.126798	-0.60912	0.005983	-0.13959	-0.21579	0.267351	-0.08623

Table 4.5: Principal Component Analysis of G10 Benchmark Long-term Government Bond Returns

	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5	Comp 6	Comp 7
Eigenvalue	6.66	1.37	0.89	0.63	0.42	0.37	0.32
Variance Prop.	60.58%	12.49%	8.08%	5.69%	3.85%	3.36%	2.87%
Cumulative Prop.	60.58%	73.07%	81.15%	86.84%	90.69%	94.05%	96.93%
Eigenvectors:	**Vector 1**	**Vector 2**	**Vector 3**	**Vector 4**	**Vector 5**	**Vector 6**	**Vector 7**
Variable							
CANGB	0.147673	-0.65534	0.283644	-0.22609	0.366077	0.530956	-0.01042
USGB	0.198147	-0.5605	0.22251	0.409355	-0.06538	-0.64766	-0.04427
BELGB	0.368586	0.130347	-0.04376	0.100306	0.114516	0.082431	-0.05517
FRAGB	0.367205	0.100443	-0.06175	0.073445	0.067877	0.010505	0.086526
GERGB	0.368297	0.152536	-0.00622	0.154609	0.149628	0.04968	0.005817
ITAGB	0.304577	-0.08011	-0.25238	-0.42673	0.028986	-0.23601	0.741869
NETHGB	0.372356	0.115043	-0.00153	0.155813	0.133434	0.038956	-0.04448
SWEDGB	0.287029	-0.08132	-0.31042	-0.55974	-0.02696	-0.25192	-0.65268
SWITGB	0.328042	0.24454	0.06605	0.274642	0.207916	0.117993	-0.0936
UKGB	0.296482	-0.18092	-0.0907	0.102078	-0.84673	0.368583	0.013355
JAPGB	0.152568	0.29533	0.831636	-0.36935	-0.20506	-0.13707	0.009291

For benchmark long-term government bonds, a similar process suggests two or three factors are also significant in explaining returns (Table 4.5). The first component appears to be a common factor. The second component differentiates between a leading US group (consisting of US-Canada and joined by Italy and

Sweden) and European group. The third component, though more clearly significant than in the equity returns-based analysis, is less interpretable. The three components together explain over 80 percent of the variation in long-term government bond returns. In the next section we take the number and nature of these components to inform the specification of a factor model for the equity and bond prices of the G10 capital markets.

4.4 Empirical Results from Factor Analysis

A technical note is required before we report our empirical results. The factor decompositions reported here are based on GMM estimation of the restricted latent factor model. The nonlinear optimisation method used minimises the sum of the squared deviations (across i and j) of $s(i,j)$[215] from the variances generated by the model. These squared deviations are more robust to failure of normality[216]. To extract the factors, we use the state-space representation of the restricted latent factor model and apply the Kalman filter estimated by Gaussian ML. The Gaussian ML estimation of the dynamic (state-space) representation of the factor model is more robust to capturing time variation in the data. Preliminary experimentation with the methodology suggests that they give very identical results. Our decompositions are therefore not affected.

4.41 Empirical Results of Factor Analysis of G10 Markets Equity Returns

We conduct a sequential estimation of our factor model to aid the nonlinear optimisation process especially for getting good starting values. We begin by estimating a version of the factor model in (4.25), which excludes the regional

[215] The variance-covariance matrix

factors. This enables us to look at only the effects of one common unobserved factor and the respective unobserved idiosyncratic factors. Despite the need for sequential estimation, this allows suitable comparison of the two cases – a return generation process purely in terms of a common unobserved factor and the main model which includes unobserved regional effects. The respective idiosyncratic factors are by construction included in both scenarios.

Table 4.51a gives the proportion of equity returns variance explained by the observed common factor, the unobserved common factor, and the residual factors for each G10 equity market. These numbers are also presented graphically in Figure 5.6 in terms of contributions to the total variance. The observed factor (movements in world stock markets) contributes on average about 43% to the variance of each of the G10 equity markets. This contribution to the overall variance is determined by the R-squared obtained from robust standard errors OLS estimation of the individual equity markets on the world stock market index[217]. This filtration process is necessary because of the composition of the world market index, which is dominated by the US stock market – The R-square from the US regression is about 64%. The residual returns have therefore been cleaned of the most common observed factor. All of the markets seemed to be well explained by the observed common except Italy which had an R-square of about 25%. We therefore feel justified that this is indeed an observed common factor.

[216] We are aware this could be regarded as inefficient because they give equal weights to all the (i, j) combinations. This is however not crucial.

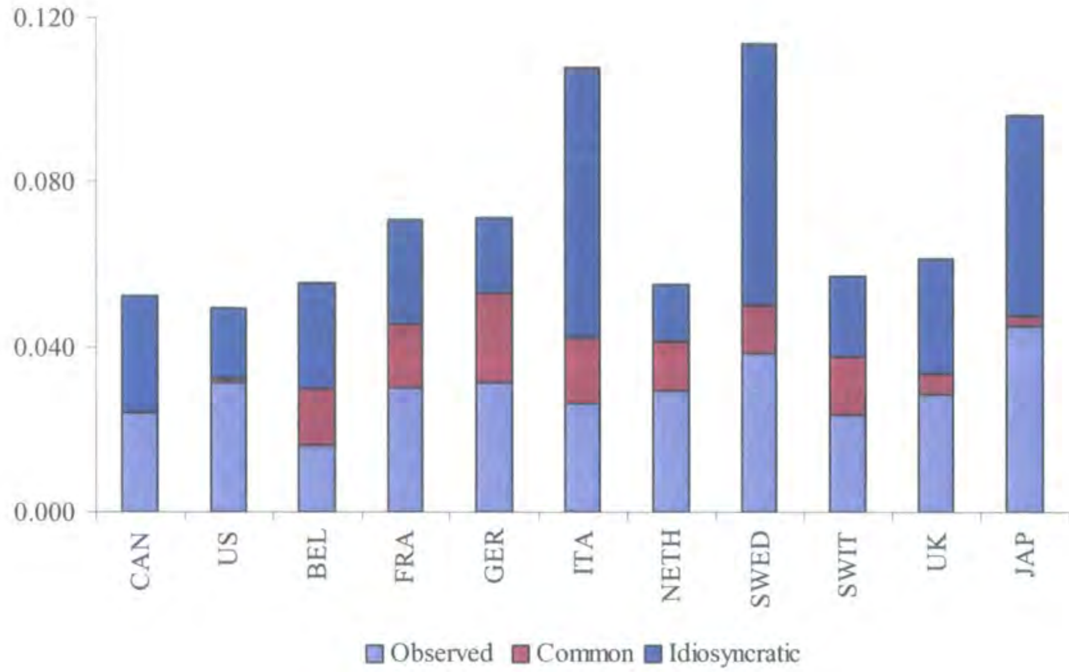
[217] Estimating models by OLS using robust (heteroscedasticity consistent) standard errors is now standard in most menu-driven econometric packages.

The unobserved common factor is more important for mainly the European equity markets (with the exception of the UK). It explains between 8 and 30 percent of the variance of the European markets whilst only up to about 3 percent for Canada, US and Japan. The unobserved idiosyncratic factor is averaging about 43 percent contribution to the overall variance of each of the markets. This suggests that substantial idiosyncrasies would remain in these markets if G10 markets equity returns were explained by only one observed factor and one unobserved factor.

Table 4.51a: Decomposition of Variance of G10 Markets Equity Returns

		Contributions to Variance		
	Variance	Observed	Common	Idiosyncratic
CAN	0.00052	45.73%	0.06%	54.20%
US	0.00050	63.80%	1.26%	34.94%
BEL	0.00056	28.84%	25.21%	45.95%
FRA	0.00071	42.93%	21.50%	35.57%
GER	0.00071	44.50%	29.99%	25.51%
ITA	0.00108	24.72%	14.48%	60.80%
NETH	0.00055	53.42%	21.94%	24.65%
SWED	0.00114	33.89%	10.29%	55.81%
SWIT	0.00057	41.49%	24.40%	34.11%
UK	0.00061	46.67%	8.15%	45.17%
JAP	0.00096	46.87%	2.77%	50.37%

Figure 4.6: Decomposition of Variance of G10 Markets Equity Returns



The results of the two-factor model decomposition suggest that further explanation of the large residual unobserved idiosyncratic factor is necessary. We therefore extend the model to include two regional factors. These factors are restricted across the G10 Equity markets. This is the trust of the hypothesis in this chapter: Are G10 equity market returns are explained by an observed world factor, a common unobserved factor, an unobserved US-regional factor, an unobserved EU-regional factor, and an unobserved idiosyncratic factor. Equation (4.25) is estimated for this The US-regional factor affects only The US stock market and the Canadian stock market and the EU-regional factor affects all the European countries. The Japanese market is not affected by either regional factor. The results are given in Table 4.51b and figure 4.7.

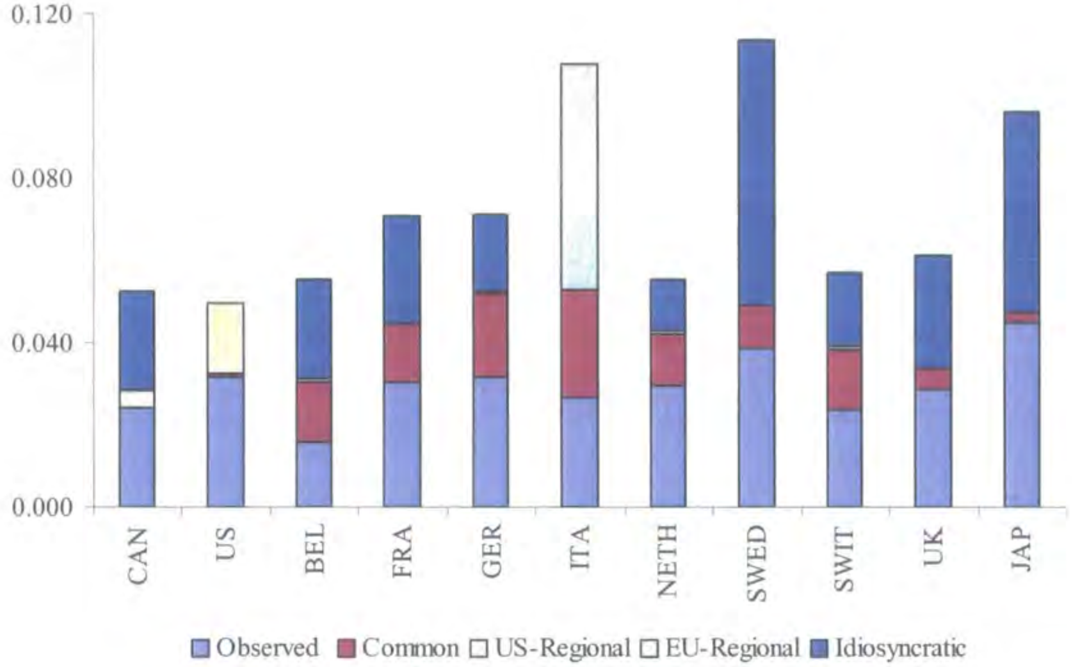
Table 4.51b: Decomposition of Variance of G10 Markets Equity Returns with Regional Factors added.

	Variance	Contributions to Variance			
		Observed	Common	Regional	Idiosyncratic
CAN	0.00052	45.73%	0.07%	8.23%	45.96%
US	0.00050	63.80%	1.32%	34.75%	0.12%
BEL	0.00056	28.84%	25.68%	1.36%	44.11%
FRA	0.00071	42.93%	20.15%	0.09%	36.84%
GER	0.00071	44.50%	28.77%	0.55%	26.17%
ITA	0.00108	24.72%	24.49%	50.76%	0.00%
NETH	0.00055	53.42%	22.76%	1.78%	22.04%
SWED	0.00114	33.89%	9.25%	0.03%	56.82%
SWIT	0.00057	41.49%	25.22%	1.80%	31.49%
UK	0.00061	46.67%	8.12%	0.32%	44.88%
JAP	0.00096	46.87%	2.54%	0.00%	50.59%

The results in Table4.51b indicate that in general, after including the two regional factors, the idiosyncratic component of the variance decreased. The average contribution of the idiosyncratic factor fell by 10% to 33% explanation of the variance of the equity returns. Although the average contribution of the unobserved common factor appears to have been unchanged, further investigation reveals some interesting facts.

The idiosyncratic component of the US stock markets has been completely removed, declining to almost zero. However, the Canadian idiosyncratic factor decreased slightly but remains substantial. The behaviour of these two markets under this factor structure suggests that whilst the US stock market is more global, strongly affected by observed world factor and the unobserved regional factor, the Canadian stock market depends on a sizable idiosyncratic factor. This result can be interpreted as evidence that US stock market and US-based companies dominates the region, which is not surprising; but the fact that there are idiosyncratic factor for Canada is evidence of some segmentation within the Canadian stock market.

Figure 4.7: Decomposition of Variance of G10 Markets Equity Returns with Regional factors added.



The European markets also reveal some interesting results. The inclusion of the regional factor seemed to have isolated the Italian stock market from the rest of Europe. The EU-regional factor appears to be an Italian stock market factor in disguise because it was very marginal for other European countries. Although this might be difficult to perceive it does suggests that when the combined group of European equity markets are examined at a regional level, the separation of the Italian equity market from the rest of the group is more apparent. This result confirms the findings obtained from figure 4.5, which clearly shows that the Italian stock market is most segmented in regional terms. This so because after the effects of the combined observed and unobserved common factors have been removed, the unobserved European regional factor only explains comovements in Italian returns. This effectively means that the other markets are much more closer to the group of countries than the Italian stock markets. As expected, the behaviour of the behaviour of the Japanese market is unaffected by this factor structure.

To investigate whether the idiosyncratic factors are truly idiosyncratic, we rewrite the model in equation (4.25) as a dynamic restricted latent factor model as given in the general state-space representation in equations (4.30) and (4.31). All the unobserved factors are extracted once the model is estimated by applying the Kalman filter. The extracted unobserved common factor, the US-Regional, and EU-Regional factors are given in Figures 4.8a, 4.8b and 4.8c. The individual unobserved idiosyncratic factors are not plotted but we provide their correlation matrix and a matrix of corresponding p-values in Tables 4.51c and 4.51d respectively.

Figure 4.8a: Extracted G10 Equity Markets Unobserved Factor(a)(b)(c)

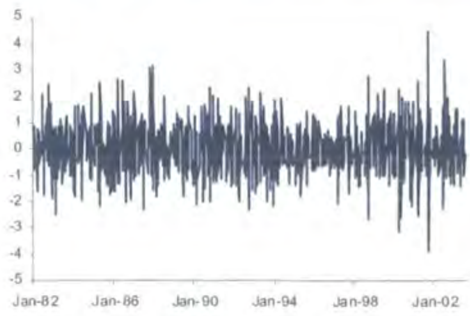


Figure 4.8b: Extracted G10 Equity Markets Unobserved US-Regional Factor(a)(b)(c)

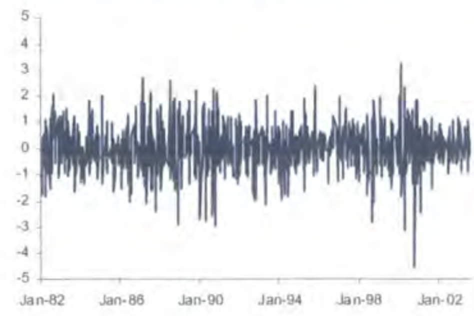
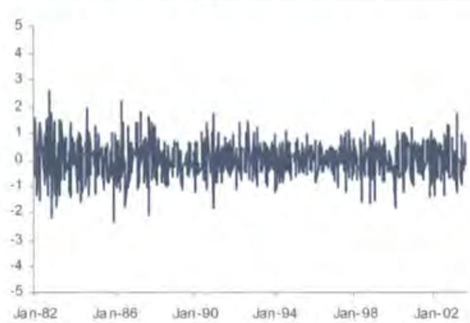


Figure4.8c: Extracted G10 Equity Markets Unobserved EU-Regional Factor(a)(b)(c)



a)Factors were extracted using the kalman filter
b) The restricted latent factor model was written in state-space form and the kalman filter was estimated by Gaussian maximum likelihood
c)The residual equity returns runs from January 1982 to August 2003.

The probability value of the calculated Lawley's chi-squared statistic for the independence of the correlation matrix is 0.0001[218]; suggesting that this matrix is not independent (diagonal) and at least one of the bilateral correlations are different from zero (significant). The critical value for significance of the individual bilateral correlations is 0.0986; obtained from Fisher's z-transform of the standard t-test of the significance of bilateral correlations. The Bonferroni-adjusted p-values of the individual bilateral correlations are given in Table 4.51d. This p-value adjusts for the fact that multiple comparisons are being made and therefore is less conservative or restrictive.

Table 4.51c: Correlation matrix of Extracted Unobserved Idiosyncratic Factor for G10 Markets Equity Returns.

[218] We report only the probability values here due to the programming routines that used. This value would be consistent with calculated statistic.

	CAN	US	BEL	FRA	GER	ITA	NETH	SWED	SWIT	UK	JAP
CAN	1										
US	-1	1									
BEL	0.0017	-0.0017	1								
FRA	-0.0042	0.0042	0.4256	1							
GER	-0.0516	0.0516	0.5153	0.3822	1						
ITA	0.0168	-0.0168	0.2688	0.2487	0.1952	1					
NETH	-0.0803	0.0803	0.4948	0.5008	0.7847	0.3961	1				
SWED	0.0300	-0.0300	0.2442	0.1401	0.1355	0.0773	0.4295	1			
SWIT	0.0434	-0.0434	0.4560	0.3652	0.5327	0.2230	0.5385	0.2578	1		
UK	0.0675	-0.0675	0.2468	0.3805	0.5073	0.3704	0.2874	0.4311	0.3420	1	
JAP	0.5890	-0.5890	0.0482	0.0090	-0.0215	-0.0666	-0.0068	-0.0344	0.0729	-0.0990	1

Table 4.51d: Probability values of bilateral correlations in the Correlation Matrix of Extracted Unobserved Idiosyncratic Factor for G10 Markets Equity Returns.

	CAN	US	BEL	FRA	GER	ITA	NETH	SWED	SWIT	UK	JAP
CAN	0.0000										
US	0.0000	0.0000									
BEL	0.9542	0.9542	0.0000								
FRA	0.8880	0.8880	0.0000	0.0000							
GER	0.0838	0.0838	0.0000	0.0000	0.0000						
ITA	0.5736	0.5736	0.0000	0.0000	0.0000	0.0000					
NETH	0.0071	0.0071	0.0000	0.0000	0.0000	0.0000	0.0000				
SWED	0.3146	0.3146	0.0000	0.0000	0.0000	0.0096	0.0000	0.0000			
SWIT	0.1456	0.1456	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		
UK	0.0236	0.0236	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	
JAP	0.0000	0.0000	0.1059	0.7632	0.4716	0.0256	0.8210	0.2484	0.0146	0.0009	0.0000

The results from Table 4.51d indicate that 56% of the individual bilateral correlations were significant whilst 44% were not. A significant correlation is a rejection of the null that the bilateral correlation is equal to zero and an insignificant correlation is a failure to reject the null. The average correlation across all the markets is 0.165. The average European market correlation is 0.253 and average of Canada, US and Japan is –0.069. These low correlations would suggest that that the residual idiosyncratic factors are indeed idiosyncratic and the markets are more integrated. There is a perfectly negative correlation between the unobserved idiosyncratic returns of the US and Canadian market, which indicate that these two markets are almost identical in the extent of their commonality with the other markets. The data has perhaps revealed the strong economic interdependence between the US and Canada.

The significant bilateral correlations appear to be mostly those between European markets, suggesting perhaps that there remain some unexplained common component in the unobservable idiosyncratic returns of European stock markets. The insignificant correlations were those between most of the European markets and Canada, US and Japan. This suggests that that G10 equity markets are clearly divided along regional lines. There is a mainly European block and a US block. Canada, US and Japan belong to the US block. The UK's bilateral correlations with Canada, US and Japan were significant suggesting that perhaps the UK belongs to both groups. Netherlands' bilateral correlations were significant for the US and Canada. Switzerland's bilateral correlation was significant for Japan. These results also have some implications for international portfolio diversification. There are still potentially substantial diversification gains to be made by the Canadian, US and Japanese investor wishing to diversify in Europe. These investors should focus on all the countries they have insignificant correlations or negative correlations with.

4.4.2 Empirical Results of Factor Analysis of G10 Markets Benchmark Long-term Government Bonds

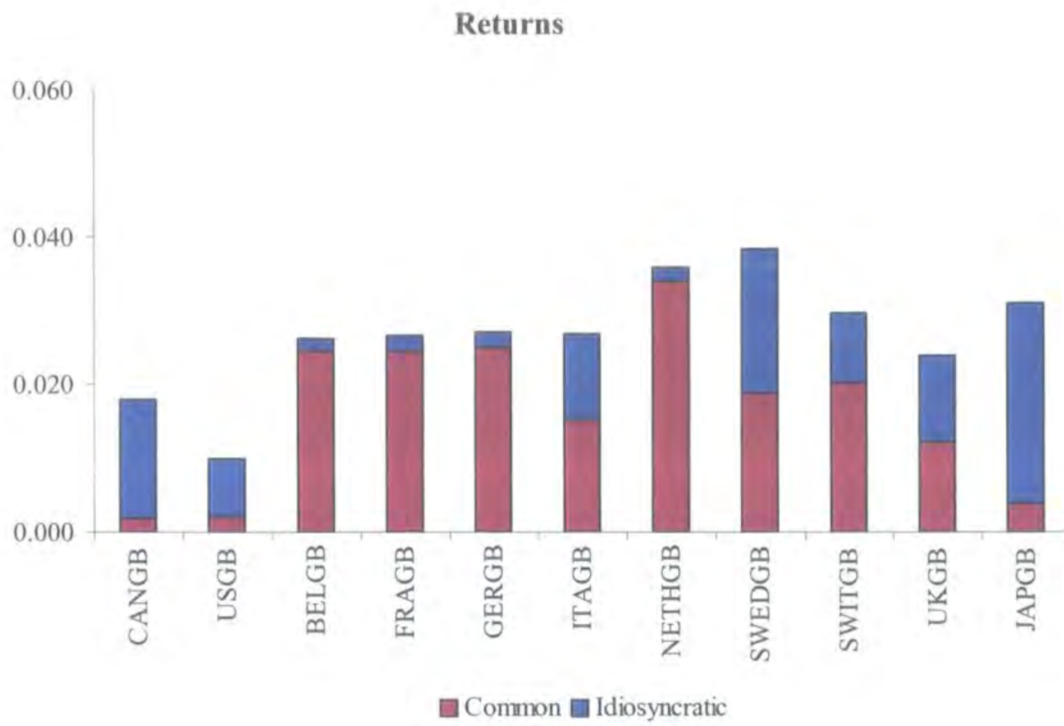
As in the case for equities, we also adopt a sequential estimation for the government bond market. There is no observable world factor for the factor model estimated because the Morgan Stanley Capital International world long-term government bond index only starts in 1999. Table4.52a and Figure 4.9 give the contribution of a common unobserved factor and the respective idiosyncratic factors to the total variance of the G10 bond markets.

Table 4.52a: Decomposition of Variance of G10 Benchmark Long-Term Government Bond Returns

		Contributions to Variance	
	Variance	Common	Idiosyncratic
CANGB	0.00018	10.02%	89.98%
USGB	0.00010	19.81%	80.19%
BELGB	0.00026	93.16%	6.84%
FRAGB	0.00027	91.98%	8.02%
GERGB	0.00027	92.68%	7.32%
ITAGB	0.00027	56.56%	43.44%
NETHGB	0.00036	94.83%	5.17%
SWEDGB	0.00038	49.01%	50.99%
SWITGB	0.00030	68.33%	31.68%
UKGB	0.00024	51.19%	48.81%
JAPGB	0.00031	12.34%	87.67%

The equity markets appear to be more volatile than the government bond market. This asymmetry is clearly seen from magnitude of the variances. The equity markets have higher variances suggesting that, possibly, the risk premium on equity is considerably higher than the risk premium on bonds over the estimation sample.

Figure 4.9: Decomposition of Variance of G10 Markets Benchmark Long-Term Government Bond



The European government bond markets appear to be strongly driven by the common unobserved factor while Canada US, and Japan are mostly driven by idiosyncratic factors. The average contribution across all markets is 58% for the unobserved common factor and 42% for the idiosyncratic factor. The result also reveals some interesting dynamics among the European countries. Italy, Sweden and UK have sizeable idiosyncratic contributions suggesting that they may not be fully integrated with the other European bond markets. The French, German, Belgian and Dutch long-term interest rate market is almost entirely driven by this unobserved common factor.

This finding is very important because it appears to confirm the anecdotal evidence on recent developments in these markets; especially with respect to the implementation of the Euro currency and the requirements for member countries wishing to adopt the Euro. UK and Sweden are not part of the Euro and, the

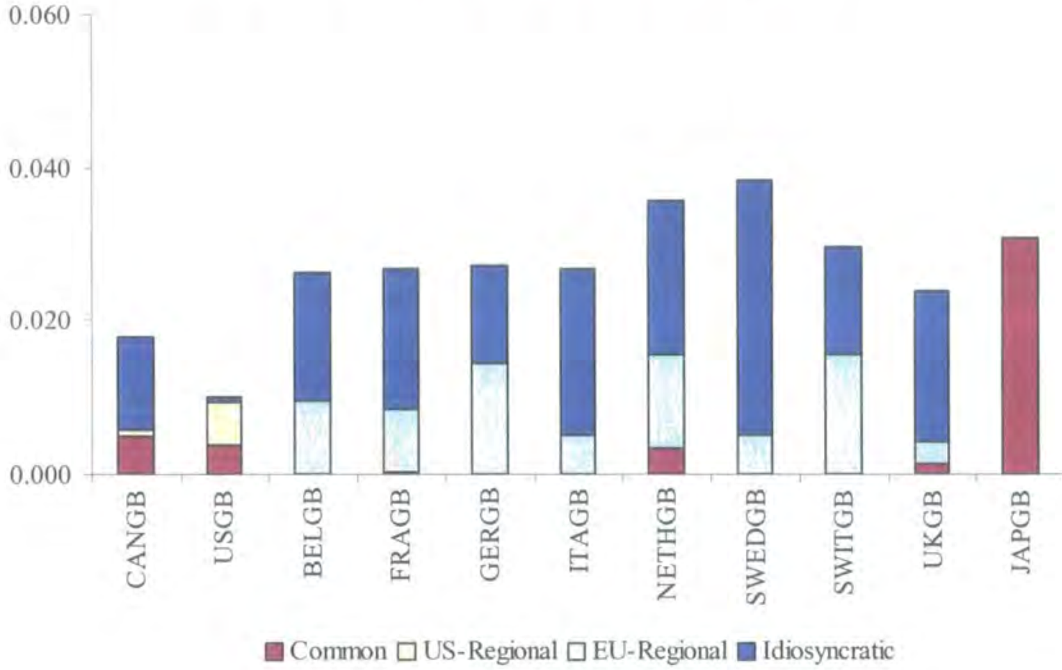
Italian government bond market has always been viewed as problematic. These issues might explain the high contribution of the idiosyncratic factor to the variance for these countries. Further investigation of the factor structure is therefore required. The factor structure that includes regional factors might provide some answers.

Table 4.52b and Figure 4.10 give the estimation result for the factor model with regional factors for the G10 benchmark long-term government bond market. The results portray a somewhat similar pattern as was for the equity markets when the regional factors were included in the model. The average residual contribution is higher than in the case of equity markets, when regional factors are added – 33% for equities and 55% for bonds; suggesting perhaps that equity markets are integrated than bond markets. The US long-term interest rate market appears to absorbing most of the US-Canada regional shocks while the Canadian market remains substantially idiosyncratic. The Japanese market on the other hand appeared to be wholly explained by the unobserved common factor.

Table 4.52b: Decomposition of Variance of G10 Markets Benchmark Long-Term Government Bond Returns with Regional Factors added.

		Contributions to Variance		
	Variance	Common	Regional	Idiosyncratic
CANGB	0.00018	27.80%	4.42%	67.77%
USGB	0.00010	37.45%	57.90%	4.65%
BELGB	0.00026	0.07%	36.28%	63.65%
FRAGB	0.00027	0.52%	31.31%	68.17%
GERGB	0.00027	0.05%	53.51%	46.44%
ITAGB	0.00027	0.06%	18.87%	81.08%
NETHGB	0.00036	9.55%	33.88%	56.57%
SWEDGB	0.00038	0.15%	12.95%	86.90%
SWITGB	0.00030	0.03%	52.39%	47.58%
UKGB	0.00024	5.64%	11.74%	82.62%
JAPGB	0.00031	98.88%	0.00%	0.00%

Figure 4.10: Decomposition of Variance of G10 Markets Benchmark Long-Term Government Bond Returns with Regional Factors added



The result is mixed for the European region. With regional factors added the idiosyncrasies within the European markets is more apparent. Firstly, with the exception of Netherlands and the UK, none the European markets are driven by shocks emanating from the unobserved common factor. The regional factor is reasonably important for all of the European markets. The sizeable increase in contribution of the idiosyncratic factor when the regional factor is added is surprising and counter-intuitive; although, Italy, Sweden and the UK did have high idiosyncratic percentage contribution in the two-factor scenario. Thus, the empirical evidence indicates that despite the regionalisation in the long-term government bond markets, unobserved idiosyncratic factors are relevant in explaining the variation in government bond market even for the core Euro currency countries in our EU-regional classification; which implies that some segmentation remains in European bond markets.

Figure 4.11a: Extracted G10 Government Bond Markets Unobserved Common Factor[(a)(b)(c)]

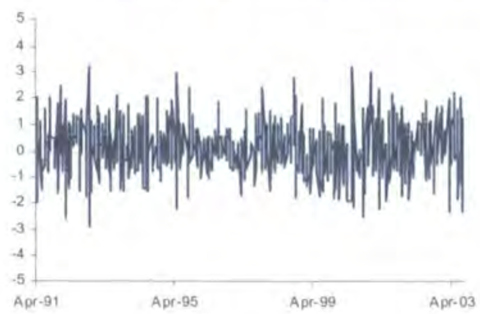


Figure 4.11a: Extracted G10 Government Bond Markets Unobserved US-Regional Factor[(a)(b)(c)]

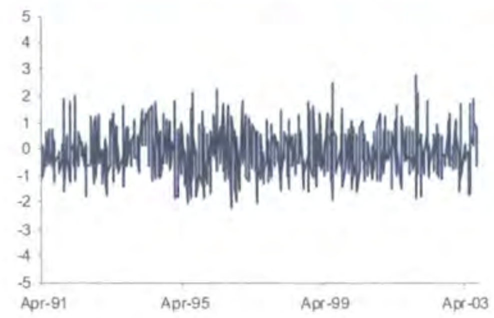
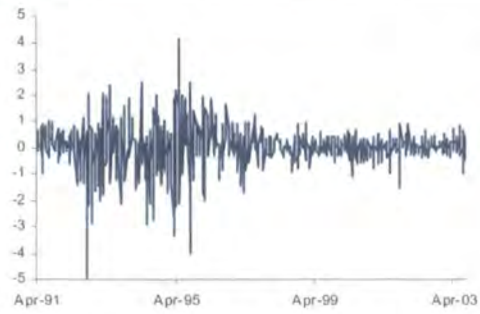


Figure 4.11c: Extracted G10 Government Bond Markets Unobserved EU-Regional Factor3[(a)(b)(c)]



a) Factors were extracted using the kalman filter
b) The restricted latent factor model was written in state-space form and the kalman filter was estimated by Gaussian maximum likelihood
c) The Bond returns runs from April 1991 to August 2003.

To assess whether the factors are truly idiosyncratic, as done in the case of the equity markets, the factor model is written in dynamic form using the general state-space representation. The Kalman filter is then applied to the system and the factors are extracted. Figures 4.11a, 4.11b and 4.11c above, plots the path of the unobserved common factor, the US-Canada regional factor and the EU-regional factor.

The respective idiosyncratic factors are not plotted. Instead, the correlation matrix of the unobserved idiosyncratic or residual factor to the G10 long-term government bond markets is given in table 4.52c. The Bonferroni-adjusted p-values of the individual bilateral correlations are given in Table 4.52d.

Table 4.52c: Correlation matrix of Extracted Unobserved Idiosyncratic Factor for G10 Markets Benchmark Long-Term Government Bond Returns.

	CANGB	USGB	BELGB	FRAGB	GERGB	ITAGB	NETHGB	SWEDGB	SWITGB	UKGB	JAPGB
CANGB	1										
USGB	-1	1									
BELGB	0.0217	-0.0217	1								
FRAGB	-0.0152	0.0152	0.9309	1							
GERGB	0.0120	-0.0120	0.9560	0.9453	1						
ITAGB	0.0182	-0.0182	0.8264	0.8154	0.8929	1					
NETHGB	0.0053	-0.0053	0.9568	0.9498	0.9765	0.8734	1				
SWEDGB	0.0406	-0.0406	0.7874	0.7274	0.8157	0.5785	0.8220	1			
SWITGB	-0.0024	0.0024	0.8563	0.8528	0.8594	0.8092	0.8627	0.7482	1		
UKGB	-0.0433	0.0433	0.7171	0.7024	0.7293	0.5611	0.7345	0.5304	0.6692	1	
JAPGB	0.0690	-0.0690	-0.0145	-0.0065	-0.0140	-0.0052	-0.0167	-0.0201	0.0313	-0.0351	1

Table 4.52d: Probability values of bilateral correlations in the Correlation Matrix of Extracted Unobserved Idiosyncratic Factor for G10 Markets Benchmark Long-Term Government Bond Returns.

	CANGB	USGB	BELGB	FRAGB	GERGB	ITAGB	NETHGB	SWEDGB	SWITGB	UKGB	JAPGB
CANGB	0.0000										
USGB	0.0000	0.0000									
BELGB	0.5823	0.5823	0.0000								
FRAGB	0.7003	0.7003	0.0000	0.0000							
GERGB	0.7608	0.7608	0.0000	0.0000	0.0000						
ITAGB	0.6443	0.6443	0.0000	0.0000	0.0000	0.0000					
NETHGB	0.8938	0.8938	0.0000	0.0000	0.0000	0.0000	0.0000				
SWEDGB	0.3039	0.3039	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000			
SWITGB	0.9525	0.9525	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		
UKGB	0.2731	0.2731	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	
JAPGB	0.0804	0.0804	0.7133	0.8685	0.7226	0.8955	0.6731	0.6104	0.4280	0.3734	0.0000

The probability value of the calculated Lawley's chi-squared statistic for the independence of the correlation matrix is 0.0001[219]; suggesting that this matrix is not independent (not diagonal) and at least one of the bilateral correlations are different from zero (significant). The critical value for significance of the individual bilateral correlations is 0.1300. The Bonferroni-adjusted p-values of the individual bilateral correlations are given in Table 4.52d. The Bonferroni-adjusted p-value adjusts for the fact that multiple comparisons are being made and it is therefore less conservative or restrictive. The average idiosyncratic correlation is 0.389. There are 55 unique individual bilateral correlations. 53% of these were significant and 47% were insignificant. The 53% significant bilateral correlations appear to have a regional basis. This is consistent with the equity markets. It suggests evidence market integration; and more importantly, regional market integration as there remains a significant unobserved common component in the unobserved idiosyncratic returns. As an extension to the current analysis we investigate the model with regional factors for equities and government for the beginning after the introduction of the euro on 1 January 1999 to end of the sample. This analysis is carried in sub-section 4.6 below.

Another important finding here is that there were almost no unobserved idiosyncratic returns in the Japanese long-term bond market (JGB bonds). The contribution of the idiosyncratic factor to the variance of the Japanese long-term government bond market return is almost zero. This result has two implications. Firstly, it shows that the JGB bonds respond almost entirely to shocks emanating from the unobserved common factor. This unobserved common factor appear to be reasonably significant for only Canada, US, Netherlands and UK. JGB bonds would therefore be more responsive to shocks emanating to these countries and is perhaps integrated with these countries. Secondly, there is complete agreement between the results from the decomposition of the variance of returns using GMM and, the correlation matrix of unobserved idiosyncratic returns, which were extracted using the Kalman filter. The GMM calculated unobserved common factor contribution to the variance JGB bonds was about 99%. The Kalman filter extracted unobserved idiosyncratic JGB bond returns were

[219] We report only the probability values here due to the programming routines that used. This value would be consistent with calculated statistic.

significantly uncorrelated with all of the extracted unobserved idiosyncratic returns in the other G10 government bond markets. We therefore feel reasonably justified in using these methodologies as it robustifies our results.

4.53 Empirical Results of Factor Analysis of a Joint Model G10 Markets Asset Returns

We consider a joint model for the filtered equity and benchmark long-term government bonds. This model provides a sophisticated extension of our methodology[220]. The model assesses the joint comovements in equity and bond markets. The model estimated is in the general form given in equation (4.29). Table 4.53, Figure 4.11 and Figure 4.12 give the contribution of the various factors to the variance in equity and bond markets.

Table 4.53: Decomposition of Variance of G10 Markets Equity and Bond Returns

		Decomposition of Variance				
	Variance	Observed	Common	Market	Regional	Idiosyncratic
CAN	0.00052	45.73%	6.86%	0.35%	6.88%	40.17%
US	0.00050	63.80%	23.51%	0.78%	0.15%	11.76%
BEL	0.00056	28.84%	15.11%	9.04%	16.30%	30.71%
FRA	0.00071	42.93%	1.26%	7.22%	15.51%	33.09%
GER	0.00071	44.50%	3.13%	8.88%	18.59%	24.90%
ITA	0.00108	24.72%	1.67%	1.20%	20.40%	52.01%
NETH	0.00055	53.42%	4.90%	10.84%	10.14%	20.70%
SWED	0.00114	33.89%	1.13%	1.38%	15.81%	47.79%
SWIT	0.00057	41.49%	11.50%	7.71%	9.50%	29.80%
UK	0.00061	46.67%	1.64%	5.21%	5.10%	41.38%
JAP	0.00096	46.87%	13.59%	39.55%	0.00%	0.00%
CANGB	0.00018	0.00%	0.66%	16.94%	83.54%	0.00%
USGB	0.00010	0.00%	0.08%	30.09%	8.18%	61.64%
BELGB	0.00026	0.00%	13.45%	61.22%	17.87%	7.47%
FRAGB	0.00027	0.00%	11.07%	60.27%	19.72%	8.95%
GERGB	0.00027	0.00%	15.45%	61.71%	15.60%	7.24%
ITAGB	0.00027	0.00%	0.11%	36.34%	30.88%	32.67%
NETHGB	0.00036	0.00%	14.16%	65.44%	15.26%	5.14%
SWEDGB	0.00038	0.00%	0.01%	29.95%	32.32%	37.73%
SWITGB	0.00030	0.00%	22.35%	43.62%	8.11%	25.92%
UKGB	0.00024	0.00%	1.87%	45.15%	6.81%	46.16%
JAPGB	0.00031	0.00%	26.62%	5.62%	0.00%	67.77%

[220] The idea for this extension is very new and would be used in future work, including applications to different classes of assets. There is however considerable increase (a cost) in estimation time, given the size the system – the number of factor and variables.

The unobserved common factor captures the joint variation in equity and bond markets and could also be viewed as a mechanism for capturing spillovers from the equity market to the bond market and vice versa. The average unobserved common factor is about 9%. The average idiosyncratic factor is about 29%. The overall common factor – combining the observed equity market factor and unobserved common factor for equities and bonds – explains about 30% of the joint variation in the equity and long-term government bond markets for the G10 countries. This is a sizeable contribution and suggests that there is a reasonable level of commonality across the two asset markets in the G10 countries.

A closer look at the decomposition of the variance reveals an interesting picture of the dynamics in international equity and bond markets. The Bond market factor is more significant than the equity market factor suggesting, perhaps, that events in the bond market are much more susceptible to the unobserved common bond market shock than the cross-asset market shock. The regional variation is important and seems to be broadly consistent with the scenario revealed when the markets were looked at separately; especially for the core Euro currency countries.

The idiosyncratic factors are a bit difficult to explain but they seem to be suggesting that the there are considerable idiosyncrasies across the markets when one considers the joint comovements in equity and bond markets. The most reasonable explanation is that despite the observed commonality across the markets, these markets are not completely integrated. Regional integration is however more important especially for the core Euro currency countries in the G10 markets group – Belgium, France, Germany and the Netherlands. To see these clearly we redo figure 4.11 in figure 4.22 without the observed equity factor. This enables a clear visualisation of the results. In the next sub-section further investigation of the regional effects is carried separately for equity and bond markets for the period (January 1999 – August 2003) after the introduction of the euro, the European Union single currency.

Figure 4.11: Decomposition of Variance of G10 Markets Equity and Bond Returns

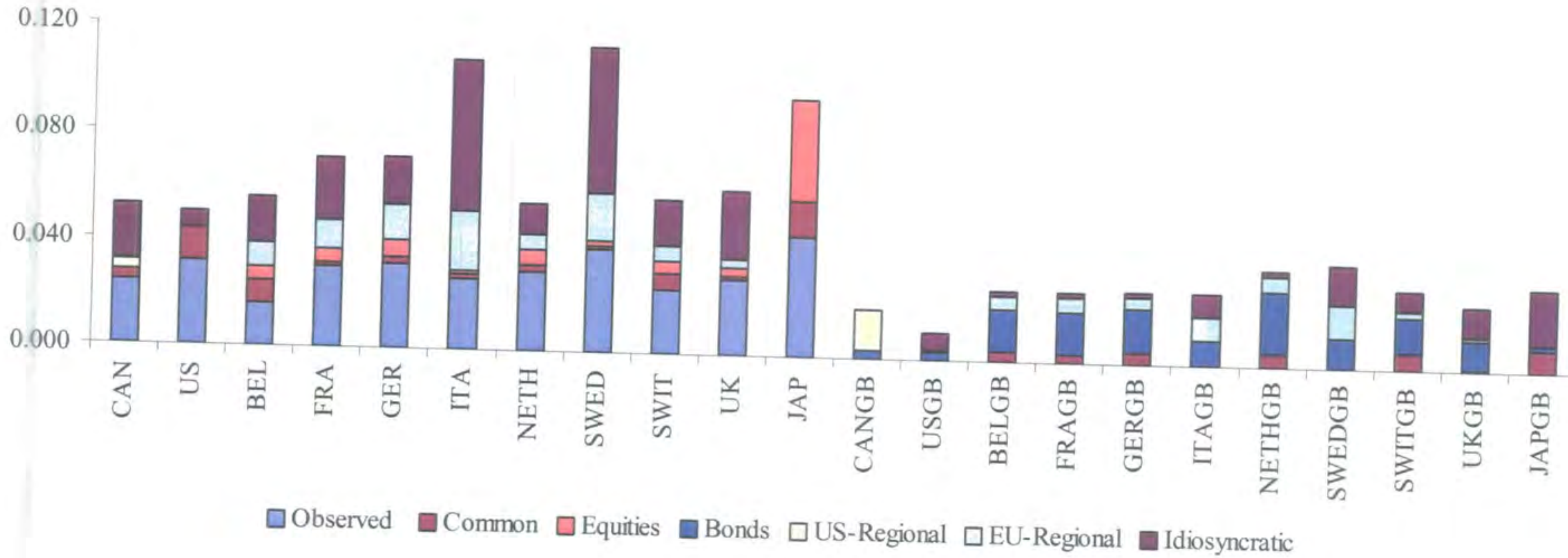
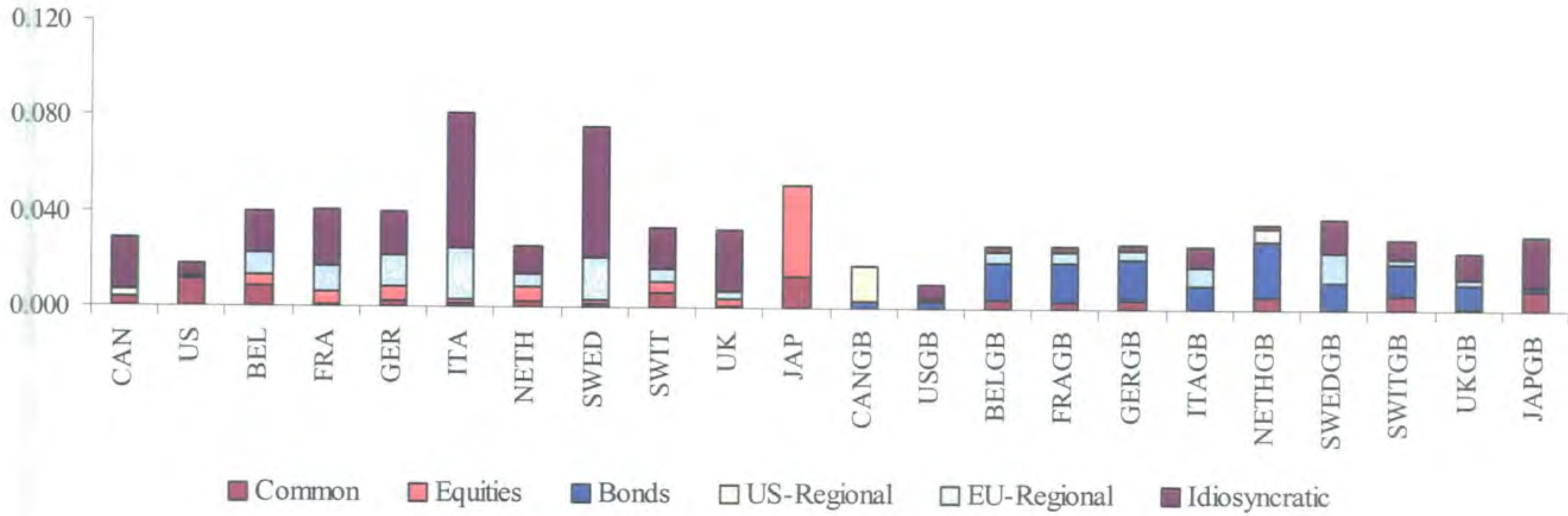


Figure 4.12: Decomposition of Variance of G10 Markets Equity and Bond Returns without the observed equity market factor



4.5 Empirical Results of Factor Analysis of a G10 Markets Asset Returns after the introduction of the euro on 1 January 1999.

In this sub-section we examine the comovements in the G10 equity markets and the G10 long-term benchmark government bond markets for period of 18 January 1999 to 8 August 2003; consisting of 240 weekly observations. This is the post euro period of our sample. The main objectives of this analysis is to assess the extent of regional influences in the G10 asset markets after the introduction of the euro and to compare the results with those obtained over the entire sample, which included the post euro period. Although a direct comparison of the two sub-periods might not appear entirely intuitive due to the huge difference in the number of observations in the two sub-periods (1126 observation for equities and 645 observations for government bonds for the entire sample), the post euro analysis would provide insights into the extent of capital market integration after the introduction of the euro. In this regard, we only estimate the factor model that includes regional factors. Due to the small number of observations over this new period, a joint stock and bonds model is not estimated. Attempts to estimate a joint model over the new period were beset with serious convergence problems in the optimisation routines primarily because of the lack observations and the number of parameters that were estimated.

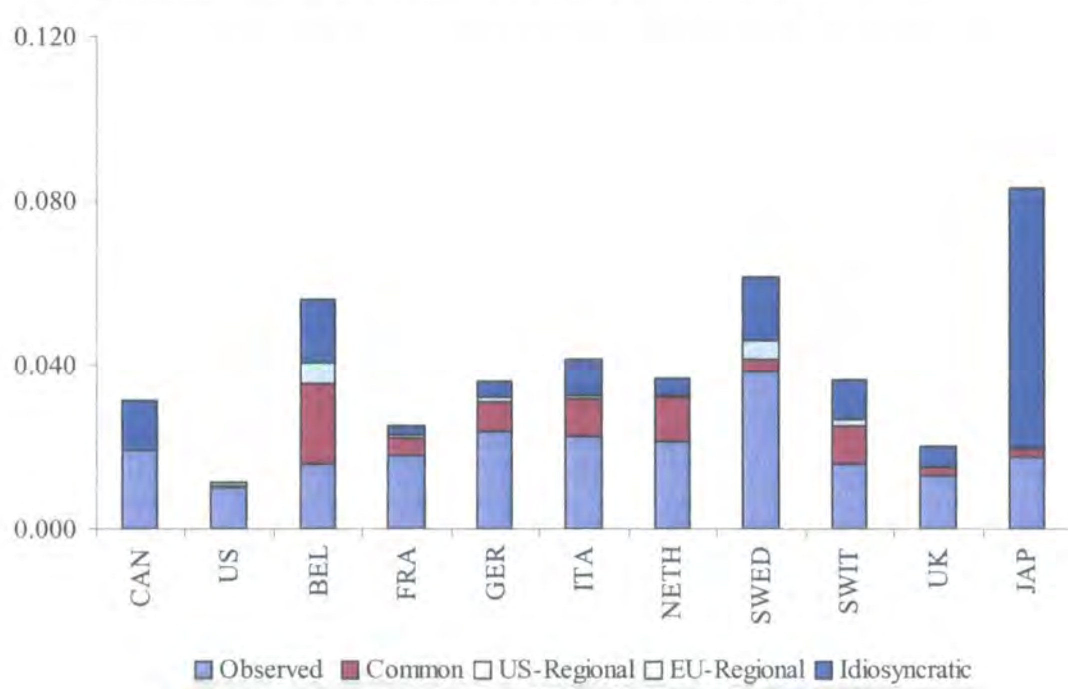
4.5.1 Empirical Results of Factor Analysis of a G10 Equity Markets after the introduction of the euro on 1 January 1999.

We re-estimate the model in equation (4.24) over the new sample period, 8 January 1999 8 August 2003. As previously, the estimation is carried out in two stages. Raw equity returns are filtered in stage one by running a robust OLS estimation for equity return regressed on a constant and the observed world factor, the world market return; and the residuals of this is equation is used as the filtered returns. In stage two, the set of filtered returns are then estimated as a restricted factor model using equation (4.25). Table 4.61a and Figure 4.13 give the contribution of the various factors to the variance in equity and bond markets.

Table 4.61a: Decomposition of Variance of G10 Markets Equity Returns with Regional Factors for the period 8 January 1999 to 8 August 2003.

		Contributions to Variance			
	Variance	Observed	Common	Regional	Idiosyncratic
CAN	0.00031	60.91%	0.55%	0.00%	38.54%
US	0.00011	87.29%	3.35%	9.34%	0.02%
BEL	0.00056	28.58%	35.18%	8.77%	27.48%
FRA	0.00025	70.68%	17.96%	2.09%	9.26%
GER	0.00036	65.92%	20.19%	3.80%	10.09%
ITA	0.00041	54.23%	22.47%	2.04%	21.27%
NETH	0.00037	58.45%	29.42%	0.81%	11.32%
SWED	0.00061	62.90%	4.41%	7.43%	25.26%
SWIT	0.00036	44.20%	24.57%	4.82%	26.41%
UK	0.00020	65.38%	9.26%	0.96%	24.40%
JAP	0.00083	21.22%	2.61%	0.00%	76.17%

Figure 4.13: Decomposition of Variance of G10 Markets Equity Returns with Regional factors for the period 8 January 1999 to 8 August 2003.



With exception of Japan, the observed world equity market factor explains over 25% of the variance of each of the G10 equity markets in the period after the introduction of the euro. The decrease in the contribution for Japan (down from 47% to 25%) is quite substantial; perhaps reflecting the poor performance of the Japanese stock markets in the last five years especially after the bursting of the dotcom bubble. The contribution of the observed factor to the variance of the euro area countries has increased over the period. This suggests that as a block, these countries are more integrated with the other G10 markets.

The average contribution of the unobserved common factor to the variance of all the G10 equity markets has stayed more or less the same; about 15% in both periods. The unobserved regional factors have all but disappeared in this new estimation period[221]. The average unobserved observed US-regional factor decreased from about 4% to 1% with Canada having no contribution to its variance from this factor over the estimation period. The average unobserved EU-regional factor decreased from 5% to 3%. However, over the entire sample period Italy was the only country capturing the effects of the unobserved EU-regional factor. In the new estimation period the, with the exception of Netherlands and the UK, a very small proportion of the variance of all of the European countries were now explained by the unobserved EU-regional factor (Table 4.61a and Figure 4.13).

The contribution of the individual unobserved idiosyncratic factors to the variance of the respective G10 markets has decreased over the new estimation

[221] Figure 5.14b and Figure 5.14c plot the extracted unobserved regional factors. We discuss these below.

period. The average contribution of the unobserved idiosyncratic factor decrease from 33% to 25%. There was a noticeable increase in the contribution of the Japanese unobserved idiosyncratic return (up from 51% to 76%), which is consistent with the contribution of the observed factor in this new estimation period. The Italian stock market can now be explained by its unobserved idiosyncratic return (21%) – over the entire sample period there was no contribution from the unobserved Italian market idiosyncratic return.

The evidence so far suggests that there has been an increase in the contribution of the observed factor to variance of all the G10 markets. The contribution of the unobserved common factor has remained the same while the contribution of the regional factors has decreased although the EU-regional factor accounts for a small proportion of the variance of the European region countries in the sample. This evidence indicates increase in the level of integration of between the G10 countries after the introduction of the euro. However, there are remains substantial idiosyncratic returns in these markets.

To fully assess the extent of capital market integration we rewrite the restricted factor model in dynamic state-space form and estimate the system by the Kalman filter algorithm. As previously, we extract the various factors and construct a correlation matrix of the extracted unobserved idiosyncratic factors. This matrix is tested for independence using Lawley's asymptotic tests of independence. The significance of the individual bilateral correlations is assessed by using Fisher's z-transform of the standard t-test of significance of bilateral correlations. We report the Bonferroni-adjusted p-values for this statistic. The extracted unobserved common factor, extracted unobserved US-regional factor and the extracted EU-regional factor are given in Figure 4.14a, Figure 4.14b and Figure 4.14c. It is interesting to note that the extracted unobserved US-regional factor is almost zero; consistent with and, confirming the results obtained in the GMM decompositions reported in table 4.61a and figure 4.13 above.

Figure 5.14a: Extracted G10 Equity Markets Unobserved Factor[a][b][c]

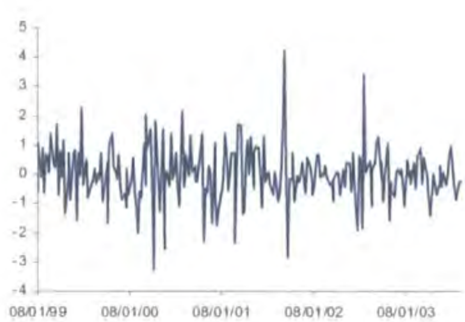


Figure 5.14b: Extracted G10 Equity Markets Unobserved US-Regional Factor[a][b][c]

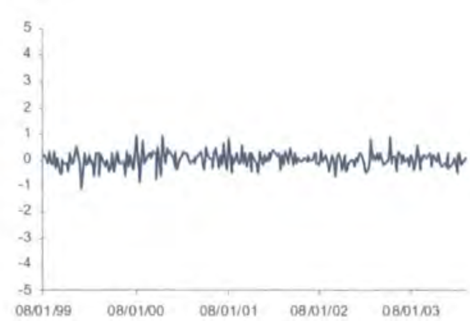
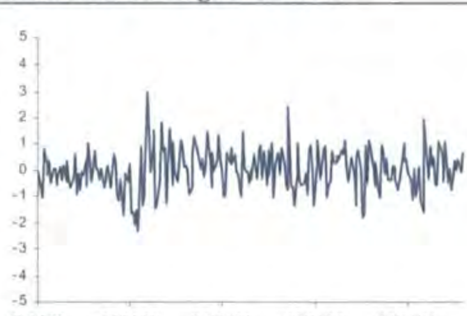


Figure5.14c: Extracted G10 Equity Markets Unobserved EU-Regional Factor[a][b][c]



a)Factors were extracted using the kalman filter
b) The restricted latent factor was written in state-space form and the kalman filter was estimated by Gaussian maximum likelihood
c)The residual equity returns runs from January 1999 to August 2003.

The correlation matrix of the extracted unobserved idiosyncratic factors is given in Table 4.61b. The Bonferroni-adjusted p-values for the significance of the individual bilateral correlations are given in Table 4.61c. Lawley's test of independence suggests that the correlation matrix is not diagonal or independent and at least one bilateral correlation is different from zero. The probability value of the calculated Lawley's chi-squared statistic for the independence of the correlation matrix is 0.0002[222]. The critical value for significance of the individual bilateral correlations is 0.0986. The average idiosyncratic correlation is 0.22. As previously, there are 55 unique individual bilateral correlations. 58% of these were significant and 42% were insignificant. The 58% significant bilateral correlations segregate on a regional basis. The unobserved idiosyncratic UK stock returns is now correlated with all of the G10 countries' suggesting that residual UK stock market returns has become more integrated with the euro-block countries and Japan since the introduction of the euro currency.

Table 4.61b: Correlation matrix of Extracted Unobserved Idiosyncratic Factor for G10 Markets Equity Returns for the period 8 January 1999 to 8 August 2003.

	CAN	US	BEL	FRA	GER	ITA	NETH	SWED	SWIT	UK	JAP
CAN	1										
US	-1	1									
BEL	0.0501	-0.0501	1								
FRA	0.0343	-0.0343	0.6351	1							
GER	-0.0071	0.0071	0.6908	0.6411	1						
ITA	-0.0383	0.0383	0.5227	0.6200	0.6067	1					
NETH	0.0426	-0.0426	0.4866	0.7211	0.7144	0.6781	1				
SWED	0.1009	-0.1009	0.6496	0.4637	0.4564	0.3523	0.5382	1			
SWIT	0.0343	-0.0343	0.2872	0.5145	0.5500	0.4975	0.3807	0.5467	1		
UK	-0.0958	0.0958	0.1648	0.4025	0.3709	0.3454	0.3404	0.3025	0.2430	1	
JAP	0.0216	-0.0216	-0.0314	-0.0347	-0.0727	-0.0550	-0.0159	-0.0746	-0.0709	-0.2451	1

Table 4.61c: Probability values of bilateral correlations in the Correlation Matrix of Extracted Unobserved Idiosyncratic Factor for G10 Markets Equity Returns for the period 8 January 1999 to 8 August 2003.

[222] We report only the probability values here due to the programming routines that used. This value would be consistent with calculated statistic.

	CAN	US	BEL	FRA	GER	ITA	NETH	SWED	SWIT	UK	JAP
CAN	0.0000										
US	0.0000	0.0000									
BEL	0.0929	0.0929	0.0000								
FRA	0.2498	0.2498	0.0000	0.0000							
GER	0.8123	0.8123	0.0000	0.0000	0.0000						
ITA	0.1995	0.1995	0.0000	0.0000	0.0000	0.0000					
NETH	0.1532	0.1532	0.0000	0.0000	0.0000	0.0000	0.0000				
SWED	0.0007	0.0007	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000			
SWIT	0.2499	0.2499	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		
UK	0.0013	0.0013	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	
JAP	0.4686	0.4686	0.2932	0.2454	0.0148	0.0655	0.5949	0.0123	0.0175	0.0000	0.0000

4.62 Empirical Results of Factor Analysis of a G10 Markets Benchmark Long-term Government Bonds after the introduction of the euro on 1 January 1999.

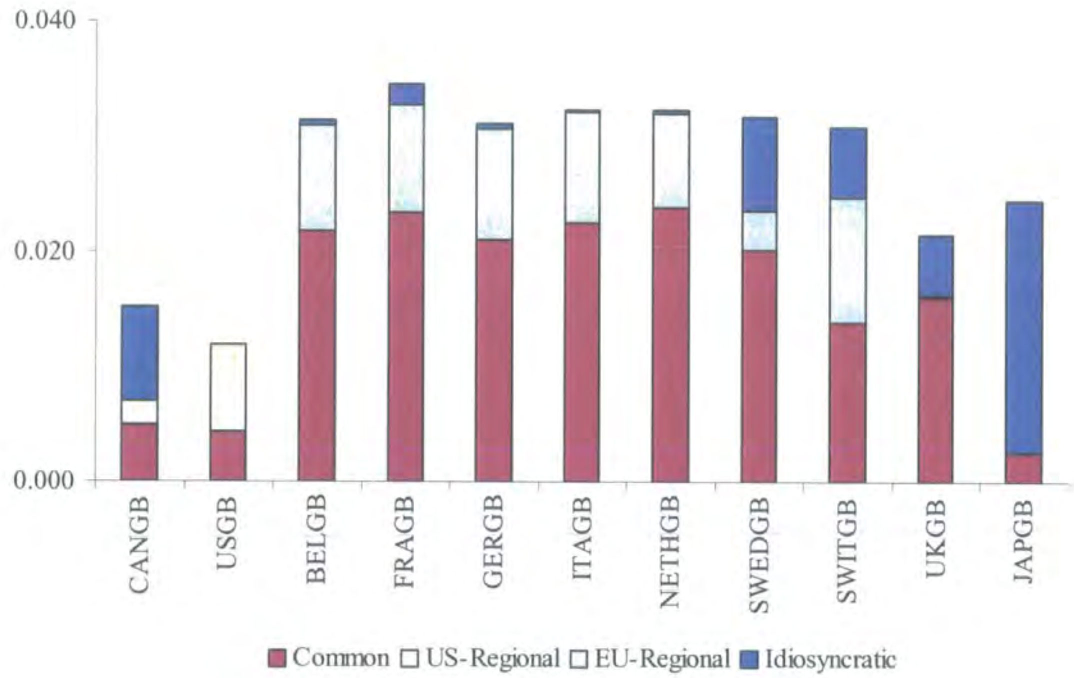
The decompositions of the variance of the G10 long-term benchmark government bond markets for the new estimation period is given in Table 4.62a and Figure 4.15. The average contribution of the unobserved common factor to variance of the government bond markets has increased from 16% over the entire sample to 55% in the period after the introduction of the euro. There has been a substantial increase in the contribution of the unobserved common factor for the euro area countries. Over the entire sample, there was little or no contribution from the unobserved common factor to the variance of the euro area countries in our sample. Since 1999, the average contribution of the unobserved common factor for euro area countries has increased from around 2% to over 69%. This confirms the empirical fact that euro area countries have a common repo interest rate[223].

Table 4.62a: Decomposition of Variance of G10 Markets Benchmark Long-term Government Bond Returns with Regional Factors for the period 8 January 1999 to 8 August 2003.

[223] A repo is short for "sale or repurchase agreement" where one party agrees to sell bonds or other financial instruments to another party with an agreement to repurchase equivalent securities in the future, under formal legal requirement (Gray (1998)). This is the interest that central bank changes from time to time. The repo rate is related to the long-term government bond yield and therefore bond prices.

	Variance	Contributions to Variance		
		Common	Regional	Idiosyncratic
CANGB	0.00015	32.57%	13.39%	54.04%
USGB	0.00012	36.47%	63.51%	0.02%
BELGB	0.00031	69.15%	29.78%	1.07%
FRAGB	0.00034	67.48%	27.22%	5.30%
GERGB	0.00031	67.80%	30.93%	1.27%
ITAGB	0.00032	69.32%	30.12%	0.57%
NETHGB	0.00032	73.69%	25.57%	0.75%
SWEDGB	0.00032	63.32%	10.95%	25.73%
SWITGB	0.00031	44.77%	35.70%	19.53%
UKGB	0.00021	75.04%	0.48%	24.48%
JAPGB	0.00024	10.39%	0.00%	89.61%

Figure 4.15: Decomposition of Variance of G10 Markets Benchmark Long-term Government Bond Returns with Regional factors for the period 8 January 1999 to 8 August 2003.



There was a small increase in the average contribution of the US-regional factor to the variance of the US and Canada government bond market (increasing 6% to 7%). The average contribution of EU-regional factor fell from 23% to 17%. There were no effects of the EU-regional factor on the UK long-term government bond market. The contribution of the EU-regional factor to the variance of the UK long-term government bond market decreased from 12% to less than 1%

confirming that UK interest rates and euro area interest rates remains apart. The average contribution of the idiosyncratic has decreased from 55% over the entire sample to 25% since the January 1999. Since the introduction of the euro, the euro currency area counties in our sample have almost no unobserved idiosyncratic returns in their long-term government bond markets. With the increase in the contribution of the unobserved common factor and the significant contribution of the EU-regional factor to the variance of most of the European countries there is evidence of bond market integration and strong regional integration in European bond markets.

As done for equities, further investigation of the evidence of integration is carried out by rewriting the restricted government bonds factor model in dynamic state-space form. The dynamic factor model is estimated using the Kalman filtering algorithm. The extracted factors are given in Figure 4.16a, Figure 4.16b and Figure 4.16c. The correlation matrix of the extracted unobserved idiosyncratic factors and, the matrix of Bonferroni-adjusted p-values for Fisher's z-transform of the standard t-test of the significance of the bilateral correlations are given in Tables 4.62b and Tables 4.62c respectively.

Figure 5.16a: Extracted G10 Government Bond Markets Unobserved Common Factor[(a)(b)(c)]

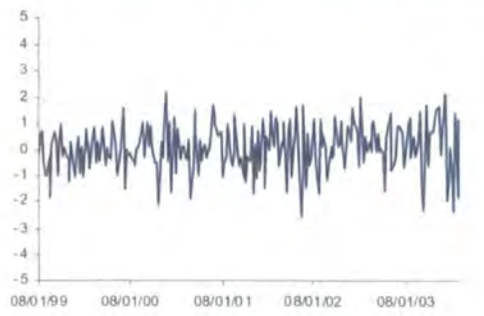


Figure 5.16b: Extracted G10 Government Bond Markets Unobserved US-Regional Factor[(a)(b)(c)]

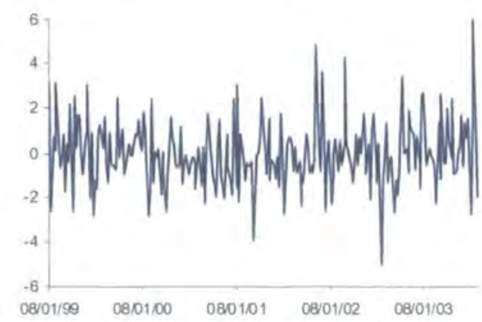


Figure 5.16c: Extracted G10 Government Bond Markets Unobserved EU-Regional Factor3[(a)(b)(c)]

a) Factors were extracted using the kalman filter
b) The restricted latent factor was written in state-space form and the kalman filter was estimated by Gaussian maximum likelihood
c) The Bond returns runs from January 1999 to August 2003.

The probability value of the calculated Lawley's chi-squared statistic for the independence of the correlation matrix is 0.0001[224]; again suggesting that this matrix is not independent (not diagonal) and at least one of the bilateral correlations are different from zero (significant). The critical value for significance of the individual bilateral correlations is 0.1300. The average idiosyncratic correlation is 0.456. There are 55 unique individual bilateral correlations. 56% of these were significant and 44% were insignificant. Consistent with equity markets, the 56% significant bilateral correlations once again segregate on a regional basis. This suggests evidence market integration;

[224] We report only the probability values here due to the programming routines that used. This value would be consistent with calculated statistic.

and more importantly, regional market integration as there remains a significant unobserved common component in the unobserved idiosyncratic returns.

After the introduction of the euro, the Japanese government bond markets (JGB bonds) have become more idiosyncratic. The contribution of the idiosyncratic factor to the variance of the Japanese long-term government bond market return Has increased from is almost 0% to almost 90%, completing reversing the results obtained over the entire sample period. This suggests that the Japanese government bond market is still outlier market. In the previous analysis it seemed to have been capturing the common factor when most of the other markets, especially the European markets were being driven by either their regional factors or their idiosyncratic factor. In the new estimation period (after the introduction of the euro) perhaps the true idiosyncratic nature of the JGB bond market is now observed.

Table 4.62b: Correlation matrix of Extracted Unobserved Idiosyncratic Factor for G10 Markets Benchmark Long-term Government Bond Returns for the period 8 January 1999 to 8 August 2003.

	CANGB	USGB	BELGB	FRAGB	GERGB	ITAGB	NETHGB	SWEDGB	SWITGB	UKGB	JAPGB
CANGB	1										
USGB	1	1									
BELGB	0.0862	0.0862	1								
FRAGB	0.0597	0.0597	0.9208	1							
GERGB	0.1057	0.1057	0.9659	0.9245	1						
ITAGB	0.1139	0.1139	0.9818	0.9313	0.9750	1					
NETHGB	0.0616	0.0616	0.9788	0.9292	0.9655	0.9840	1				
SWEDGB	0.0208	0.0208	0.8190	0.7827	0.8404	0.8270	0.8147	1			
SWITGB	0.0486	0.0486	0.6988	0.6772	0.6929	0.6966	0.7305	0.5468	1		
UKGB	-0.1341	-0.1341	0.8845	0.8287	0.8936	0.8904	0.8574	0.6819	0.7024	1	
JAPGB	-0.0602	-0.0602	0.0212	-0.0205	0.0292	0.0112	0.0020	-0.0174	0.0589	-0.0508	1

Table 4.62c: Probability values of bilateral correlations in the Correlation Matrix of Extracted Unobserved Idiosyncratic Factor for G10 Markets

Benchmark Long-term Government Bond Returns for the period 8 January 1999 to 8 August 2003.

	CANGB	USGB	BELGB	FRAGB	GERGB	ITAGB	NETHGB	SWEDGB	SWITGB	UKGB	JAPGB
CANGB	0.0000										
USGB	0.0000	0.0000									
BELGB	0.0290	0.0290	0.0000								
FRAGB	0.1306	0.1306	0.0000	0.0000							
GERGB	0.0074	0.0074	0.0000	0.0000	0.0000						
ITAGB	0.0039	0.0039	0.0000	0.0000	0.0000	0.0000					
NETHGB	0.1185	0.1185	0.0000	0.0000	0.0000	0.0000	0.0000				
SWEDGB	0.5975	0.5975	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000			
SWITGB	0.2187	0.2187	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		
UKGB	0.0007	0.0007	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	
JAPGB	0.1272	0.1272	0.5921	0.6040	0.4601	0.7768	0.9596	0.6602	0.1354	0.1979	0.0000

4.6 Conclusions

This chapter has analysed the comovements in G10 equity and long-term government bond markets by combine the two existing methodologies found in the empirical factor modelling literature on international asset pricing. To examine the extent of capital market integration in the G10 markets, an observed and a latent factor model were estimated. Preliminary cluster analysis and principal component analysis reveals some interesting dynamics about the interactions between these markets, which were rigorously analysed by the innovative factor modelling technique we proposed here. The factor modelling methodology proposed is comprised of a two-stage estimation process. In stage one; raw asset returns are filtered in by some filtration process. In stage two; the filtered asset returns are modelled as a dynamic restricted latent factor model using GMM and the Kalman filter. The factors are also extracted to conduct further analysis. For our purposes, we filter the equity returns by estimating a robust OLS regression of each return series on a constant and the world stock market portfolio. The residuals from this regression are modelled as a dynamic factor model. Due to the lack of a representative world benchmark long-term government bond index the bond returns were not filtered before we estimated the restricted dynamic factor model. Our focus in this chapter is on the contribution of each of these factors to the variance of the respective asset markets hence a restricted factor structure is suggested. Some factors affects all markets but with different magnitude while some factors only affect certain markets but with different magnitude as well.

The results of the analysis conducted in this chapter suggest the following:

- Both equity returns and bond market data suggest that the G10 capital markets can be broadly partitioned into US-Canada and European groups.
- Regional integration is more important for the bond market than for the equity markets as the unobserved EU-regional factor is more pronounced for the bond markets than for the equity markets.
- Substantial idiosyncrasies remain in both markets, which suggest that the markets may not be fully integrated.
- The joint estimation suggests evidence of some spillover effects between the G10 equity markets and G10 long-term bond markets.
- After the introduction of the euro area currency, European equity markets have become more integrated with world equity markets.
- After the introduction of the euro area currency, the unobserved EU-regional factor is no longer important for the euro area countries equity markets but remains important for the euro area long-term benchmark government bond markets
- Substantial idiosyncrasies still remain in the G10 equity and long-term bond markets despite the introduction of the euro are currency. Analysis of the

extracted idiosyncratic factor confirms our inference of strong regional integration as opposed universal capital market integration.

The implication of the above facts is that despite the increased globalisation of capital market the evidence of segmentation suggests that there are still reasonable diversification benefits to be obtained from international portfolio diversification and asset allocation. This can be seen from the high number of insignificant residual unobserved idiosyncratic returns in both equity and bond markets. G10 markets investors' in search of diversification benefits should focus on those countries with which their domestic markets have very low or negative unobserved idiosyncratic correlation. The results are also important for international financial stability monitoring. Regulators or central bankers involved in macro-prudential assessments would find empirical results in the chapter very useful especially the average estimates reported (Borio (2003)). The average correlation between returns gauges the collective impacts of shocks in financial markets. The extent of the comovements between the markets would inform on the potential for propagation of shocks across the markets and the likelihood of systemic risks across these markets. The next chapter focuses on the conditional correlation analysis of sectoral equity markets in UK, US and the European region in order to assess the extent of volatility spillovers between these groupings.

APPENDIX 4.1

The modified likelihood ratio test (MLRT) of equality of several covariance matrices

MLRT[225] jointly tests the equality of equality of population covariance matrices.

The test is based on the following hypotheses:

$$H_0: \quad \Sigma_1 = \Sigma_2 = \cdots = \Sigma_k == \Sigma$$

$H_1: \quad \Sigma_i \neq \Sigma_j$ with i and j ranging from 1 to k.

Σ_i or Σ_j are the respective population covariance matrices.

To implement the test, replace the population covariance matrices with their sample analogues S_i, in the above hypothesis.

The MLRT statistic is chi-squared distributed with p(p+1)(k+1)/2 degrees of freedom:

$$Mh \sim \chi^2_{p(p+1)(k-1)/2}$$

(A1.1)

Where: $M = (n-k)\ln|C| - \Sigma(n_i - 1)\ln|C_i|$;

$$h = 1 - \frac{2p^2 + 3p - 1}{6(p+1)(k-1)}\left(\Sigma\frac{1}{n_i - 1} - \frac{1}{n-k}\right);$$

$$C_i = \frac{S_i}{n_i - 1}; \quad C = \frac{\Sigma(n_i - 1)C_i}{n-k} = \frac{\Sigma S_i}{n-k};$$

p = the dimension of the covariance matrices

k = the total number of covariance matrices

[225] The test is based on Bartlett's modification of the likelihood ratio statistic for the equality of covariance matrices. For a theoretical background and some proofs, Anderson (1984) and references therein.

n_i = the number of observations in the data series generating each of the respective covariance matrices. If all the individual series have equal number of observations h becomes:

$$h = 1 - \frac{2p^2 + 3p - 1(k+1)}{6(p+1)(k-1)}$$

APPENDIX 4.2

The Kalman Filter

The Kaman filtering algorithm was proposed by Kalman (1960, (1961, (1963). The algorithm has been widely used in control and electronics engineering but only came to prominence in economics and finance in the 1980's. Very detailed descriptions of the technique are provided in foe example, Snyder (1985), Burmeister, et al. (1986), Diebold (1989), Aoki and Havenner (1991), Lutkepohl (1993), Harvey (1993), Harvey, et al. (1994), Hamilton (1994a, b), Wells (1996), Gourieroux and Monfort (1997), Kim and Nelson (1999) and Koopman, et al. (1999). The algorithm is a useful of extracting signals from data. The model is written down in general state-space form, a system of two vector equations with a linear transition from one period to the next; and it links observed and unobserved variables in the following way[226]:

$$x_t = \phi x_{t-1} + v_t \quad \text{Transition equation} \quad \text{(A2.1)}$$

$$y_t = C_t x_t + \varepsilon_t \quad \text{Measurement equation}^{227} \quad \text{(A2.22)}$$

The vector x_t is the state vector of the system; its dimension is $k \times 1$. The transition equation describes the dynamics of the state vector containing the unobserved variables. The vector contains the information about the system at time t. ϕ is a $k \times k$ matrix known as the *transition matrix*. v_t is a mean zero normally distributed random disturbance term to the system with covariance matrix equal to Q. These are also assumed to be uncorrelated in time. A2.1 is a

[226] Although the variables used are different, the structure used here is the same as in the main text. We use the basic general form here for illustrative purposes. More sophisticated representations of the system, including writing the system in lead form, is found in Koopman, et al. (1999). The intuition is however the same.

stochastic first-order difference equation. It is assumed that the initial state x_0 and it covariance matrix, P_0 are known.

The measurement or observation equation (A2.2) links the state vector to the vector containing the observed variables, y_t. C_t is a $1 \times k$ and ε_t is a normally distributed scalar disturbance term. This error term is also assumed to be serially uncorrelated. Kalman (1963) refers to $C_t x_t$ as the "message" of the system. The signal therefore consists of message, which is stochastic, plus noise. In a multivariate system, C_t becomes a matrix (C_t') and the errors will be multinormally distributed: $\begin{pmatrix} v_t \\ \varepsilon_t \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} Q & 0 \\ 0 & H \end{pmatrix}\right)$. The coefficient matrices, ϕ and C_t (or C_t'), and the variance-covariance matrices are estimated by Gaussian Maximum Likelihood – maximising the likelihood function of the system in A2.1 and A2.2.

The Kalman filter algorithm is an iterative process – the Kalman recursion. It involves prediction, updating, and mean-squared error (MSE) calculation. The iteration at time t, is given by the following loop:

Prediction step

If we assume that we have an estimate of the state, denoted as $\hat{x}_{t-1}$, in $t-1$, based on the information set in $t-1$. This estimate has a variance equal to P_{t-1}.

[227] This is also known as the observation equation.

To estimate x_t based on $\hat{x}_{t-1}$, we use, $\hat{x}_{t|t-1} = T\hat{x}_{t-1}$. The variance of the prediction error is therefore: $P_{t|t-1} = TP_{t-1}T' + Q$.

Updating step

The best estimate of the observed variables is: $\hat{y}_{t|t-1} = C\hat{x}_{t|t-1}$ with prediction error of $u_t = y_t - \hat{y}_{t|t-1} = C_t(x_t - \hat{x}_{t|t-1}) + v_t$. The variance of the prediction error is $F_t = ZP_{t|t-1}Z' + H$.

MSE

The MSE of the estimate of the state, $\hat{x}_{t|t-1}$, is the variance of its prediction error is therefore: $P_{t|t-1} = TP_{t-1}T' + Q$. The MSE of the estimate of the observation, $\hat{y}_{t|t-1}$ is the variance of its prediction error $F_t = ZP_{t|t-1}Z' + H$

As each observation is normally distributed, the Log likelihood function for the entire sample is: $\sum_{t=1}^{T} \ln L_t = \frac{n}{2}\ln(2\pi) - \frac{1}{2}\ln|F_t| - \frac{1}{2}u'F_t^{-1}u_t$. All asymptotic MLE theory is applicable here.

CHAPTER FIVE

INTERNATIONAL VOLATILITY SPILLOVER EFFECTS IN THE UK STOCK MARKET: AN EXAMINATION OF VOLATILITY SPILLOVERS FROM SELECTED US AND EUROPEAN INDUSTRIES

5.1 Introduction

In a recent Journal of Monetary Economics paper Schwert (2002) suggested that the recent episode of high volatility in US stock market is driven by a potential number of factors but perhaps by mainly sectoral market volatility, especially volatility in the technology sector. The question of idiosyncratic volatility or non-market-wide volatility is increasingly being considered as an explanation of the increasingly high equity market volatility that has been observed recently. Campbell, et al. (2001) have shown that between 1962 and 1997 there was a noticeable increase in firm-level volatility relative to market volatility. In other words, although aggregate stock markets volatility has tended to return to a long-run average level, firm-level volatility has not. An assessment of the effects of non-market-wide volatility is therefore a very important research question.

The last empirical chapter sought to explain the dynamics of factors driving the comovements in international financial markets. It establishes that international asset markets are broadly partitioned along regional lines. The objective of this chapter is to take a closer look at the UK stock market and assess, at a sectoral level, the international and regional effects of UK stock market volatility and correlations. In particular, it considers the issue of conditional, or time-varying, correlations and conditional volatility spillovers across international stock markets from the perspective of a UK investor. In this respect, higher capital market integration is synonymous with increased time-varying correlations, as well as more volatility spillovers, between markets and sectors.

More specifically, the paper firstly uses the dynamic conditional correlation (DCC) model developed by Engle (2002) to extract the time-varying conditional correlations between the UK, US and European stock markets and selected sectors. This methodology represents a significant advancement in international correlation modelling. Secondly, it investigates conditional market and sector volatility spillovers into the UK stock market. The transmission of volatility from the US and European sectors to the UK stock market is assessed in a multivariate generalized autoregressive conditional heteroscedasticity (MVGARCH) methodology using the BEKK model of Engle and Kroner (1995).

The question of what drives international financial market correlations or volatility remains very topical among both practitioners and academics alike. This issue is critical because of the role played by correlations and volatility in determining the return generating process of asset returns[228]. Establishing the link between correlation and volatility has not been straightforward despite the seemingly simple mathematical relationship between the two[229]. However, empirical evidence suggest that in periods of high stock market volatility, correlations between asset returns tends to increase relative to periods of normal

[228] This is easily deduced by looking at for example a simple one factor model of return on an asset expressed as a function of the market model for example. Capturing the co-variation between the asset and the market involves estimating the correlation between them. In fact, beta the measure of risk in the simple factor model is described as a measure of the correlation between the asset and the market portfolio.
[229] We show the theoretical link between correlations and volatilities in Appendix 1.

volatility; see for example, Gerlach and Smets (1995), Eichengreen, et al. (1996) and a report by the Bank for International Settlements' Committee on the Global Financial System (CGFS) in 1999[230]. Longin and Solnik (1995) have also shown that stock market volatility is highest when stock index returns are falling; known as a *bear market* in financial markets. Recent financial market turbulence such as the Collapse of the Russian bond market and Asian financial crises illustrates the importance of accurately determining the structure of international asset returns. An Idea of the structure of international stock returns would aid the determination of critical turning points in international financial markets. This is particularly important for risk managers or portfolio managers who compute risk measures such as Value at Risk (VaR) or Expected shortfall (tail loss)[231] on their portfolios because, they rely on the estimates of correlations between returns on financial instruments in their portfolios and on the volatility of those returns. If correlations do not change over time or if there is sufficient data to allow them to be estimated accurately determining the correlation structure of asset returns would be less daunting[232]. Loretan and English (2000b) have suggested that the changes in correlations could be due to nothing more than the 'natural and predictable effects in fluctuations in asset returns volatility'. The problem facing

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[230] CGFS (1999)

[231] Generally speaking, VaR and ES are related to market risk: VaR is the single estimate by which an institution's position in a risk category could decline due to market movements during a given holding period. Mathematically, VaR, written as $VaR_q(X)$ = the probability q that the loss will exceed an amount X over a given period. Under assumptions of normality, $VaR_q = \mathrm{E}(r_t) + Z_q \cdot \delta_r$ where Z_q corresponds to the quantile (return) associated with q. ES is the expectation (i.e. the mean) of the losses under the condition that the VaR threshold has already been broken. See for example Duffie and Pan (1997), Jorion (1997) and Tsay (2002).

[232] It was shown in the previous chapter through formal statistical test that asset correlations in G10 markets are typically unstable over both overlapping and non-overlapping samples between 1982 and 2003. This confirms existing empirical evidence from Kaplanis (1988) and Longin and Solnik (1995). A number of reasons, potentially explaining why correlations breakdown, have been put forward including structural breaks in the data or the mechanisms that determine asset

risk managers in such cases, according to Loretan and English (2000b), 'should be less difficult, as the empirical challenge then consists of modelling the time-varying nature of asset return volatilities'.

It has also been claimed by some, including for example, LeRoy and Porter (1981) and Shiller (1981), that there is 'excess volatility' in financial markets; primarily because, stock prices are too volatile to justified by changes in economic fundamentals. Although we do not seek to explore whether there is excess volatility in international financial markets, our assessments of the international sectors that drive UK stock market volatility would allow us to isolate the most influential European and US sector which affects UK stock market volatility. Output from this analysis would be invaluable in the assessments of risks to UK Financial stability emanating from erratic international stock market behaviour. The potential risks for financial stability from financial asset price volatility have been a subject for concern in recent years. Time-varying correlation estimates would be very useful in identifying turning points in the UK and international stock markets. These turning points characterise the cyclical nature of international financial market correlations and volatility.

To extract the time-varying (conditional) correlations between the UK stock markets and the selected US and European sectors and, between the UK sectors and US and European sectors, we rely on the dynamic conditional correlation (DCC) model suggested by Engle (2002a). The model represents a very recent

returns. See for example, Eichengreen, et al. (1996), Drazen (1998) and Forbes and Rigobon (2002) advancement in international correlation modelling. The transmission of volatility from the US and European sectors to the UK stock market is assessed in a multivariate generalised autoregressive conditional heteroscedasticity (MVGARCH) model. Our starting point for this analysis is the model of Engle and Kroner (1995) and the volatility spillover method suggested in Antoniou, et al. (2003). These methodologies are discussed in detail later. The rest of the chapter is organised as follows: section 5.2 briefly overviews the question of excess volatility in financial markets, the theory suggested by some of those wishing to explain recent stock market volatility[233]; section 5.3 provides an overview of ARCH and GARCH models and discusses the estimation methodologies used in this chapter; section 5.4 discusses the data; section 5.5 presents the empirical results; and section 5.6 concludes.

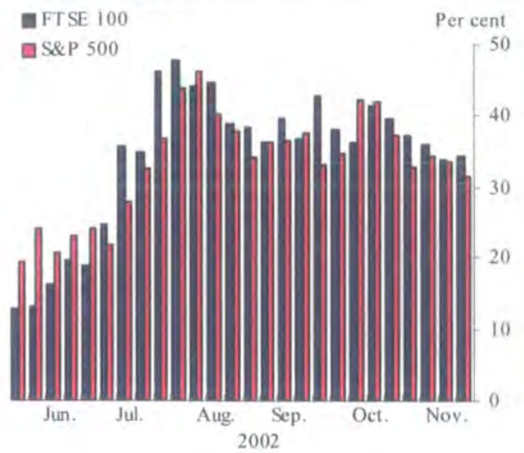
5.2 Excess volatility in the equity markets

Whether measured by the variation in past prices or the expected variation reflected in prices of traded options, stock market volatility remains very high by historical standards (Figure 5.1a & Figure 5.1b)[234]. During 2002 for example, daily historical market volatility has reached a high of 53% compared to a long-term average of around 23%.

[233] See for example Shiller (2002).

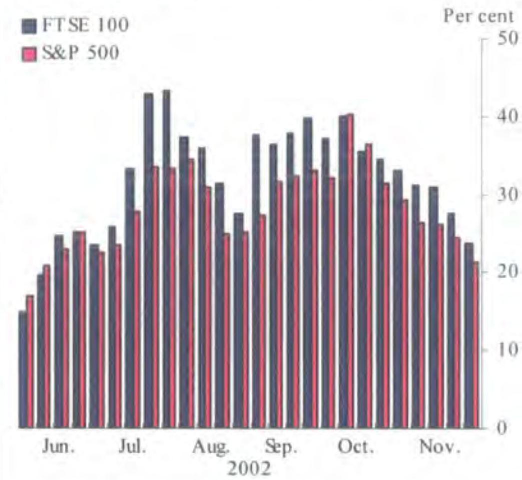
[234] Implied volatility is the market's assessment of the underlying asset volatility as reflected in the option price. The option pricing for formula, usually calculated using the Black-Scholes model (B-S) or Cox-Ross-Rubinstein binomial model, is inverted to determine the volatility implied by the market price. The B-S option pricing equation for example, gives the fair price of an option as a function of the price of the underlying asset, the option's strike price and time to expiration, the risk-free interest rate and the volatility of the underlying asset. Of all these variables, only the volatility of the underlying is not observable (and must therefore be estimated). See Mayhew (1995), Hull (2000) and Chance (2001) for further details.

Figure 5.1a: Weekly historical equity market volatility[a]



(a) Historical volatility calculated as 52-week rolling standard deviation of log returns of the FTSE100 and S&P500

Figure 5.1b: Weekly implied equity market volatility[a]



(a) Implied volatility on call options issued on the FTSE100 and S&P500. Source: Bloomberg.

Some, for example LeRoy and Porter (1981) and Shiller (1981), have argued that stock index prices are too volatile to be justified by subsequent changes in fundamentals[235]. Where market prices fully reflect all publicly available information, the stock price is equal to the discounted value of all expected future dividend payments. The variability of prices should therefore mirror the variability of expected future dividends, changes in discount rates and changes in risk aversion. Volatility that cannot be explained by these fundamentals is termed 'excess volatility'. Assuming constant discount rates (and constant risk aversion), Shiller (1989) shows that between 1871 and 1979, the S&P500 index, the main US stock market index, was about five and half times as variable as dividends. It seemed implausible that changes in dividend, discount rates or risk aversion could account for this discrepancy. However, recent academic literature has highlighted a number of fundamental factors that might explain stock volatility. These include the arrival of unanticipated information (affecting expected

[235] Additional synthesis of the excess volatility question can be found in Shiller (1989), LeRoy and Steigerwald (1995), LeRoy (1996), Campbell, et al. (1997) and Shiller (2002).

returns); or stock market overreaction to news about earnings, Aiyagari and Gertler (1998), Osband (2002); increased financial leverage, Black (1976), Schwert (1989a) Hardouvelis (1990) and Chan and Kogan (2002); the effects of sectoral volatility or firm specific volatility (affecting discount rates), Campbell, et al. (2001) and Schwert (2002); and, the time-varying nature of investor risk aversion caused by, for example, changes in investor consumption patterns, Abel (1990), Campbell and Cochrane (1999) and Chan and Kogan (2002); and the effects of financial market liquidity, Subrahmanyam (1994), Pastor and Stambaugh (2003), Chordia and Subrahmanyam (2003) and Houweling, et al. (2003). Non-fundamental factors have also been suggested. They include the existence of speculative bubbles in financial markets and investor sentiment based on mainly irrational factors, Barberis, et al. (2001) and Shiller (2002). It is however important to note that, Campbell, et al. (1997) Osband (2002) have shown that if one allows for the possibility that risk parameters evolve or change over time, one can could account for 'excess volatility'. Campbell, et al. (1997) for example noted that, "it is now clearly understood that a rejection of constant-discount rate models is not the same as a rejection of the Efficient Market Hypothesis" and "that expected returns are time-varying rather than constant".

These factors not withstanding, historically, volatility tends to return to its long-run average. This suggests that current high stock market volatility will at some point fall back. However, to the extent that current volatilities are driven by non-fundamental factors, predicting the timing of such falls is problematic. The time-varying correlations charts produced in this chapter could be used for gauging turning points in international financial markets.

5.3 Methodological Issues

The methodology of this chapter relies on the conditional volatility (risk) measures developed by the joint 2003 economics Nobel laureate Robert Engle. Engle (1982) developed the autoregressive conditional heteroscedasticity (ARCH) model and Bollerslev (1986) developed the generalised ARCH (GARCH) model. The time-varying correlation method used are based on the dynamic conditional correlation (DCC) proposed model proposed by Engle (2002a) and the correlations extracted from the BEKK MVGRACH model of Engle and Kroner (1995)[236]. The volatility spillover model is based on the BEKK MVGRACH model of Engle and Kroner (1995). This model has been applied in studies of volatility transmission by for example, Karolyi (1995) and Kearney and Patton (2000) amongst others[237]. The next sub-section will present a brief overview of ARCH and GARCH models and will discuss MVGARCH models[238], which have been used to determine conditional correlations between return series. The estimation methodology is outlined after this discussion.

5.3.1 The Basics ARCH and GARCH Models

5.3.1.1 Univariate ARCH and GARCH Models

The starting point for understanding ARCH and GARCH models is to note that conditional first moments, mean (expected return), and second moments,

[236] BEKK was originally due to versions of a working paper by Baba, et al. (1990) and Baba and et al. (1991).
[237] Sophisticated MVGARCH-type models have been applied to asset returns generally or in terms of spillovers of some form by for example, Chan, et al. (1992), Engle and Susmel (1993), Susmel and Engle (1994), Lin, et al. (1994) Koutmos and Booth (1995), Koutmos (1996), Ramchand and Susmel (1998a), Ng (2000) and Antoniou, et al. (2003).
[238] This review is not intended to be exhaustive. Extensive review of ARCH and GARCH models can be found in for example, Bollerslev, et al. (1992), Bera and Higgins (1993), Bollerslev, et al. (1994) and Poon and Granger (2003).

volatility (risk) forecasts, are preferable to their unconditional counterparts. Unconditional mean forecasts generally have a greater variance than the conditional mean. For example, if we assume that we are in a world with no uncertainty but where the expected returns on assets fluctuates over time, due perhaps to changes in inflation; the conditional variance is the difference between the expected return and the actual return (which can be zero in certain circumstances). If we use the conditional mean, the conditional variance would be zero. The unconditional mean on the other hand suggests that risk fluctuate systematically. Therefore, the conditional return is a more accurate measure of asset returns[239].

The data generating structure of ARCH and GARCH models is identical to simple ARMA processes of a random variable[240]. ARCH models assumes that the conditional variance of the innovation term is time-varying and models this term as an autoregressive process (AR) to the p-order; an AR(p) process: $\varepsilon_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\varepsilon_{t-2}^2 + \cdots + \alpha_p\varepsilon_{t-p}^2 + v_t$; where v_t is also white noise process. An ARCH process would be present in this AR (p) process of the innovations if at least one of the coefficients of the sequence is non-zero. When this is the case, the disturbance is described as: $\varepsilon_t \sim ARCH(p)$. The number of non-zero coefficients determines the order of the ARCH process. To guarantee that $\varepsilon_t^2 > 0$, v_t must be bounded from below by $-\alpha_0$ which, implies that the error term of the ARCH sequence, v_t, cannot be Gaussian or normal. An

239 The econometrics times series book by Enders (1995) reviews these issues.

240 The alternative to ARCH volatility models discussed in the theoretical finance literature is the stochastic volatility model. In these models the variance is specified to follow some latent

alternative formulation gets around this problem rather neatly: the ARCH sequence is rewritten as $\varepsilon_t = \sqrt{\alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \cdots + \alpha_q \varepsilon_{t-p}^2} \circledast w_t$; where w_t and ε_{t-1} are independent and, w_t is iid with its mean value $\mathrm{E}w_t = 0$ and its unconditional variance $\mathrm{E}w_t^2 = 1$. This implies that the expected value of the squared innovations is equal to its conditional variance: $\mathrm{E}_{t-1}\varepsilon_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \cdots + \alpha_q \varepsilon_{t-q}^2 = \sigma_t^2$. Therefore, w_t does not affect the distribution of the error term, ε_t, since both means are zero and the unconditional variance is constant..

GARCH processes follow an autoregressive moving average (ARMA) process. Bollerslev (1986) generalises the basic ARCH process to include a mixture of autoregressive and moving average terms. The basic GARCH process is given as $\varepsilon_t = w_i (\sigma_t)^{\frac{1}{2}}$ and the conditional variance is $\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$; where the variance of $w_t = \sigma_v^2 = 1$. This is the Basic GARCH (p, q) model with p indicating the order of the ARCH process and q the order of the GARCH process. If the disturbance term in a time series model follows a GARCH process, $\varepsilon_t \sim GARCH(p,q)$; it means that the conditional mean of the disturbance is equal to zero, $\mathrm{E}_{t-1}\varepsilon_t = 0$, and the conditional variance is autoregressive, $\mathrm{E}_{t-1}\varepsilon_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_p \varepsilon_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_q \sigma_{t-q}^2$. The unconditional mean is equal to zero, $\mathrm{E}u_t = 0$, and the unconditional

stochastic process. Further details are available in Hull and White (1987), Kim, et al. (1998) and Shiryaev (1999).

variance is constant, $Eu_t^2 = \sigma^2$. The most straightforward model to generate a GARCH disturbance would be:

$\varepsilon_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \cdots + \alpha_p\varepsilon_{t-p}^2 + \beta_1\sigma_{t-1}^2 + \cdots + \beta_q\sigma_{t-q}^2 + v_t$, where v_t is white noise. As in the case of the ARCH process, the order of the GARCH is determined by the number of significant coefficients. To guarantee that $\varepsilon_t^2 > 0$, v_t must be bounded from below by $-\alpha_0$ which implies that v_t cannot be Gaussian. The alternative formulation, which express the disturbance as a square-root process multiplied by an iid disturbance with zero mean and unit variance:

$\varepsilon_t = \sqrt{\alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \cdots + \alpha_p\varepsilon_{t-p}^2 + \beta_1\sigma_{t-1}^2 + \cdots + \beta_q\sigma_{t-q}^2} \bullet w_t$; gets around this problem. This implies that $Ev_t = 0$ and $Ew_t^2 = 1$. Therefore, the conditional variance of the disturbance process will now be:

$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \cdots + \alpha_p\varepsilon_{t-p}^2 + \beta_1\sigma_{t-1}^2 + \cdots + \beta_q\sigma_{t-q}^2$.

ARCH and GARCH models are estimated by maximum likelihood. ARCH and GARCH models are estimated by maximum likelihood (ML). The BHHH[241] algorithm is normally used. The residuals of time series model defined by GARCH process are assumed to follow a conditional Gaussian (normal) distribution. Experience however shows that the conditional distribution for these error terms most often have heavier tails than the conditional Gaussian distribution[242]. Two heavy-tailed distributions have been used as possible alternatives: the generalised error distribution (GED) and the student t

[241] This is due to the non-linear estimation techniques suggested by Bernt, et al. (1974). Conditional volatility models are also estimated by quasi maximum likelihood methods, GMM, Bayesian methods and indirect estimation methods. See Pagan (1996) for more details. We discuss an example of indirect estimation methods in the Appendix.

distribution[243]. We use a student t version of the BEKK MVGARCH model in our analysis. This is discussed further below.

A number of extensions to the basic GARCH models have been suggested. For example, the effects of leverage have been taken into consideration in GARCH models. Leverage terms allow for the modelling of asymmetric effects of positive and negative returns. This is important because in stock returns, negative shocks may have a larger impact on volatility than positive shocks – the so-called "good news" and "bad news" asymmetric impact on stock returns. Black (1976) suggests that bad news tends to drive down stock price, thus increasing leverage of the stock and causing the stock to be more volatile[244]. To capture this leverage effect, Nelson (1991) suggested the exponential GARCH (EGARCH) model, Glosten, et al. (1993) suggested the GJR-GARCH model which include threshold effects in the basic GARCH formulation, Zakoian (1994) suggested the ZARCH or TGARCH model which also accounts for threshold effects, which, in actual fact, is the same as the GJR-GARCH model. Ding, et al. (1993) also proposed a power GARCH (PGARCH) model, which is a more general threshold GARCH model. Engle and Ng (1993) proposed a neat way of portraying leverage effects in the form of a *news impact curve*[245]. There are also GARCH models that allow the conditional variance to influence the mean process; first suggested by Engle,

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[242] This means that the error terms contains outliers

[243] The non-normality of asset returns was discussed in chapter 2.

[244] Leverage here refers to debt-equity ratio. When firms take on increased leverage, this increases the risk faced by equity holders.

[245] The news impact curve is a functional relationship between conditional variance at time t and the shock term (error term) at time t-1, holding constant the information dated at t-2 and earlier, and with all lagged conditional variance evaluated at the level of the unconditional variance (Engle and Ng (1993)).

et al. (1987) and was dubbed the ARCH-M/GARCH-M model or ARCH/GARCH-in-the-mean Model[246].

Another recent extension to the basic GARCH model is the long memory GARCH model. The high persistence in financial time series modelled as basic GARCH processes suggests, perhaps, that they may be very close to a unit root process. Long memory GARCH models are related to the integrated GARCH (IGARCH) model discussed in Engle and Bollerslev (1986) and Nelson (1990). The IGARCH model is a GARCH process with a unit root. The unconditional variance of a unit root process does not exist. To circumvent this problem Baillie, et al. (1996) considered a *fractionally differenced process (fractionally integrated GARCH (FIGARCH) model)* instead of a fully integrated GARCH model. Bollerslev and Mikkelsen (1996) have shown that FIGARCH models are stationary[247].

When ARCH/GARCH models are fitted, diagnostic tests are required to ensure the model's appropriateness. A preliminary test is required to check whether the data is characterised by conditional heteroscedasticity – a test for autocorrelation and heteroscedasticity. After fitting the model, further diagnostic tests are required to ensure the suitability of the model. It turns out that we can use the same tests before and after fitting the model to test for autocorrelation in the residuals. The basic diagnostic test for ARCH effects is a simple Lagrange

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[246] These extension of the standard GARCH models are reviewed in Bollerslev, et al. (1994)
[247] Detailed description of this model can be found in the collected volume by Engle (1995). There are also other aspects of GARCH processes that we have not attempted to review here. These include for example the issues relating to the temporal aggregation of GARCH processes. This is the theoretical observation that if a GARCH model is correctly specified in for one

Multiplier (LM) test constructed on the basis of the conditional variance equation. The null hypothesis is that there are no ARCH effects in the residuals, which means that all the coefficients on lagged residual terms in the conditional variance equation is insignificant. Engle (1982) suggests writing the simple LM test as: $LM = T \cdot R^2 \sim \chi^2(p)$; where T is the sample size and R^2 is computed from the conditional variance equation. The test follows an asymptotic Chi-square distribution. The standard test for autocorrelation in the residuals of a model is Ljung-Box statistic (LB or Q-statistics): $Q(k) = N(N+2)\sum_{s=1}^{k} \frac{\rho_s}{N-k}$; where ρ_s is the autocorrelation to order of s, and N is the number of observations. Provided the data is written as a stationary ARMA process, $Q(k) \sim \chi_k^2$, the LB statistic follows an asymptotic chi-square distribution. The null hypothesis here is that there is no autocorrelation in the residuals[248]. In most applied work, this test is actually carried out on the standardised residuals and squared standardised residuals. The standardised residuals are the residuals divided by the conditional variance. It is also normal practice to check the distribution of the residual series against the standard normal distribution. Several tests are available for this but the most widely used is the test based on skewness and kurtosis suggested by Jarque and Bera (1980):

frequency of data, then it will be mispecified for data with different time scales (Engle and Patton (2001)). Further details can be found in Drost and Nijman (1993) and Engle (1995).

[248] It is important to note that this test was first devised by Box and Pierce (1970)

$JB = \frac{T-k}{6}(S^2 + \frac{1}{4}(K-3)^2)$; where T is the number of observations, k the number of parameters, S and K are the skewness and kurtosis[249].

5.3.1.2 Multivariate GARCH Models

The literature on multivariate GARCH (MVGARCH) models is also growing, both theoretical and empirical. Once again, we will only briefly discuss them here. Multivariate extensions of GARCH models are very important because by construction they allow the researcher to extract time-varying covariances and correlations. Time-varying covariances and correlations are very useful for conditional asset pricing models. One of the first to use an MVGARCH model in applied work was Engle, et al. (1984). In an MVGARCH model, the general k-dimensional process is given as[250]:

$$\varepsilon_t = z_t H_t^{1/2} \qquad \textbf{(5.1)}$$

where z_t is a k-dimensional iid process with zero mean and a covariance matrix, which is equivalent to the identity I_k. As in the univariate GARCH case this is the unit variance iid variable that is multiplied by the GARCH square-root of the GARCH variance. From (5.1) it follows that $\mathrm{E}\left[\varepsilon_t \middle| \Omega_{t-1}\right] = 0$ and $\mathrm{E}\left[\varepsilon_t \varepsilon_t' \middle| \Omega_{t-1}\right] = H_t$; where Ω_{t-1} is the information set in

[249] Skewness and kurtosis were described in the previous empirical chapter. For the conditional variance equation, skewness is: $S = \frac{\mathrm{E}[(\sum_{i=1}^{n}\varepsilon_t)^3]}{\sigma_e^3}$ and kurtosis is: $K = \frac{\mathrm{E}[(\sum_{i=1}^{n}\varepsilon_t)^4]}{\sigma_e^4}$;
where the terms in the denominators are the conditional standard deviations raised to power 3 and 4 respectively.

[250] Some of the discussion in this sub-section loosely follows brief summary of MVGARCH models given in Franses and van Dijk (2000).

the previous period. Specifying the covariance matrix H_t is the major task in MVGARCH modelling. This is due to the fact that elements of this matrix should be modelled as a function of lagged error terms and lagged and its own lags, the lagged conditional covariance matrix H_{t-1}. A number of specifications have been put forward. Only a very brief discussion is offered here[251]. The starting point for MVGARCH modelling is the *vech model*, which uses a vech operator or transformation, $vech(\cdot)$ to stack the lower triangular of the symmetric matrix H_t. Therefore, $vech(H_t)$ contains all the unique elements of H_t. The GARCH (1, 1) equivalent of an MVGARCH (bivariate or two variables in this case) model is written as:

$$vech(H_t) = W^* + A_1^* vech(\varepsilon_{t-1}\varepsilon'_{t-1}) + B_1^* vech(H_{t-1}) \qquad \textbf{(5.2)}$$

where W^* is a $k(k+1)/2 \times 1$ vector and A_1^* and B_1^* are $(k(k+1)/2 \times k(k+1)/2)$ matrices. Engle and Kroner (1995) refer to this general representation of MVGARCH models as the *vec* model. The advantage of this general representation is its flexibility because it allows all the elements of H_t to depend on all the elements of cross products of ε_{t-1} and all the elements of the lagged covariance matrix H_{t-1}. The disadvantage, however, is, the number of parameters in (5.2) increases considerable as the MVGARCH dimension increases. There are $(k(k+1)/2)(1+2(k(k+1)/2)$ parameters in a

[251] Detailed discussions of MVGARCH models can be found in Bollerslev, et al. (1988), Baba, et al. (1990), Bollerslev, et al. (1992), Bera and Higgins (1993) Bollerslev, et al. (1994), Engle (1995), Engle and Kroner (1995), Pagan (1996), Engle (2001a), Engle (2002a, b) and Morillo and Pohlman (2002). For a very recent non-technical survey of MVGARCH models see Bauwens, et al. (2003).

MVGARCH model[252]. In a two variable case there are 21 parameters to be estimated[253]. A second drawback of the vech model is problem of imposing the condition of positive semi-definiteness on the conditional covariance matrix H_t. To ensure positive semi-definiteness of the conditional covariance matrix H_t Bollerslev, et al. (1988) suggested using the diagonal-vec model. In this model the coefficient matrices A_1^* and B_1^* in (5.2) are constrained to be diagonal. The conditional covariance matrix is given as:

$$H_t = W + A_1 \odot (\varepsilon_{t-1}\varepsilon'_{t-1}) + B_1 \odot H_{t-1} \qquad \textbf{(5.3)}$$

where the symbol $\odot$ stands for the Hadamard product: that is, an element-by-element multiplication. All the coefficient matrices have dimension $k \times k$. By construction, the matrices in (5.2) are set as $A_1^* = diag(vech(A_1))$ and $B_1^* = diag(vech(B_1))$ in (5.3). The number of parameters estimated in this model is $3(k(k+1)/2)$. In the bivariate case for

[252] Parameters in the MVGARCH model are of the order k^4.

[253] The two variable form of the vech MVGARCH model is written as:

$$\begin{pmatrix} h_{11,t} \\ h_{12,t} \\ h_{22,t} \end{pmatrix} = \begin{pmatrix} \omega_{11}^* \\ \omega_{12}^* \\ \omega_{22}^* \end{pmatrix} + \begin{pmatrix} \alpha_{11}^* & \alpha_{12}^* & \alpha_{13}^* \\ \alpha_{21}^* & \alpha_{22}^* & \alpha_{21}^* \\ \alpha_{31}^* & \alpha_{32}^* & \alpha_{33}^* \end{pmatrix} \begin{pmatrix} \varepsilon_{1,t-1}^2 \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}^2 \end{pmatrix}$$

$$+ \begin{pmatrix} \beta_{11}^* & \beta_{12}^* & \beta_{13}^* \\ \beta_{12}^* & \beta_{22}^* & \beta_{23}^* \\ \beta_{31}^* & \beta_{32}^* & \beta_{33}^* \end{pmatrix} \begin{pmatrix} h_{11,t-1} \\ h_{12,t-1} \\ h_{22,t-1} \end{pmatrix}$$

example, there will be only 9 parameters to be estimated[254]. The model has an advantage because the restriction imposed on the coefficient matrices (being symmetric) insure the conditional covariance matrix H_t is symmetric and positive semi-definite. The diagonal-vec model is considered to be restrictive because it does not allow the conditional variance of one series to depend on the other variables in the system.

The next class of MVGARCH model is the BEKK model formalised in Engle and Kroner (1995). This model are expressed in quadratic forms to ensure that the MVGARCH model is positive definite – no need to constrain the parameters because the quadratic form will be positive definite. We discuss the model in detail below.

All the MVGARCH models discussed so far allow for time varying correlation structure in the covariance matrix. However, as we have seen, the number of parameters increases considerably as the MVGARCH dimension increases. Bollerslev (1990) suggests using a constant conditional correlation structure (CCC) when fitting MVGARCH models. CCC-MVGARCH model assumes that

[254] This model will take the following form:

$$\begin{pmatrix} h_{11,t} \\ h_{12,t} \\ h_{22,t} \end{pmatrix} = \begin{pmatrix} \omega_{11}^{*} \\ \omega_{12}^{*} \\ \omega_{22}^{*} \end{pmatrix} + \begin{pmatrix} \alpha_{11}^{*} & 0 & 0 \\ 0 & \alpha_{22}^{*} & 0 \\ 0 & 0 & \alpha_{33}^{*} \end{pmatrix} \begin{pmatrix} \varepsilon_{1,t-1}^{2} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}^{2} \end{pmatrix} + \begin{pmatrix} \beta_{11}^{*} & 0 & 0 \\ 0 & \beta_{22}^{*} & 0 \\ 0 & 0 & \beta_{33}^{*} \end{pmatrix} \begin{pmatrix} h_{11,t-1} \\ h_{12,t-1} \\ h_{22,t-1} \end{pmatrix}$$

the conditional correlations between the elements of ε_t are time invariant. The conditional covariance in the CCC framework is written as:

$$H_t = diag\left(\sqrt{h_{11,t}}, \ldots, \sqrt{h_{NN,t}}\right) R \; diag\left(\sqrt{h_{11,t}}, \ldots, \sqrt{h_{NN,t}}\right) \quad \textbf{(5.4)}$$

where the time invariant correlation matrix is defined as: $R = \begin{bmatrix} 1 & \cdots & \rho_{1N} \\ \vdots & \cdots & \vdots \\ \rho_{1N} & \cdots & 1 \end{bmatrix}$; where ρ_{ij} is the correlation between the variables.

(5.4) can be written in compact form as: $H_t = D_t^{1/2} R D_t^{1/2}$. For a two-variable CCC-MVGARCH model, the conditional covariance matrix is written as:

$$H_t = \begin{pmatrix} \sqrt{h_{11,t}} & 0 \\ 0 & \sqrt{h_{22,t}} \end{pmatrix} \begin{pmatrix} 1 & \rho_{12} \\ \rho_{12} & \end{pmatrix} \begin{pmatrix} \sqrt{h_{11,t}} & 0 \\ 0 & \sqrt{h_{22,t}} \end{pmatrix} \quad \textbf{(5.5)}$$

The individual conditional variances in (5.5) are assumed to follow a univariate GARCH (1, 1) process: $h_{ii,t} = \omega_{ii} + \alpha_{ii}\varepsilon_{i,t-1}^2 + \beta_{ii}h_{ii,t-1}$. For the conditional covariance matrix in (5.6) to be positive definite, the univariate GARCH (1, 1) process produce positive conditional variances and the correlation matrix R should be positive definite.

Although the CCC-MVGARCH model provide a good simplification of MVGARCH models, especially in terms of the computational requirements, and have been used widely, see fore example, Bollerslev (1990) and Baillie and Bollerslev (1990) for currency markets, Karolyi (1995), Koutmos and Booth (1995), Koutmos (1996) and Theodossiou, et al. (1997) for equity markets; it is clear that correlations on asset returns do change over time, see for example

Longin and Solnik (1995)[255]. A good time-varying correlation structure is therefore required. Traditionally, researchers have fitted MVGARCH models and extracted bivariate correlations from the estimated variance-covariance matrix. The vec model and BEKK MVGARCH model have been natural choices for this task[256]. In addition to time-varying correlations extracted from the general class of BEKK MVGARCH models, a number of other time varying correlations models have been suggested. Pourahmadi (1999) for example suggested applying Cholesky decomposition on the conditional covariance matrix because it does not requires parameters to be constrained for the matrix to be positive definite. Description of this methodology including good empirical applications can be found in Tsay (2002). Tse and Tsui (2002) suggest a using a vech representation in an MVGARCH model in which the conditional correlation matrix follows ARMA process. Recently a new class of time-varying correlations model – the DCC model – have suggested by Engle (2002a). This model is less restrictive than the CCC-MVGARCH model. We adopt the DCC approach in this chapter and the model is described in detail in the next section. Another recent advancement in MVGARCH modelling is the flexible MVGARCH (FlexM-GARCH) approach suggested by Ledoit, et al. (2003). The authors offer an algorithm that decentralises the estimation of the coefficient matrices in the original vech model of Bollerslev, et al. (1988). Instead of estimating all coefficients simultaneously, the Flex-Model estimates each element of the coefficient matrices separately and, after estimation, the conditional covariance matrix is modified so that it is positive semi-definite. According to Ledoit, et al.

[255] Tse (2000) proposed a Lagrange multiplier statistic to test constant correlation coefficients in MVGARCH models.

(2003) FlexM-GARCH model handles high-order MVGARCH systems than most of its counterparts. When applied to large portfolio selection problems and international asset pricing, GARCH models often offers an improvement but the FlexM-MVGARCH model was judged to have performed better all the other GARCH models used.

MVGARCH models can also be estimated in a factor modelling framework. These models known as factor GARCH models and orthogonal GARCH models, have been discussed in for example, Diebold and Nerlove (1989), Engle, et al. (1990b), Ng, et al. (1992a), Harvey, et al. (1992), Sentana (1998), Alexander (2001), Sentana and Fiorentini (2001), Alexander (2002) and van der Weide (2002). The methodology used here is similar to the factor modelling technique used in the previous empirical chapter. Factor GARCH models are fitted in the following three steps: a) select the first few principal components that explain a high percentage of the variance of the residuals; b) build a volatility model for the selected principal components; and c) related the volatility of each residual series to the volatilities of the selected principal components. Factor GARCH model reduce the dimension of the MVGARCH model while maintaining the accuracy of the model, Tsay (2002).

Conditional covariance matrix can also be generated from an exponentially weighted moving average (EWMA) volatility model. An EWMA model is an indirect estimation of a GARCH model. This model is widely used by

[256] Note that the vec model does not guarantee non-negative definiteness of the variance covariance matrix whilst the BEKK MVGARCH model does. Parameter restrictions are also required for the variance-covariance matrix in the vec model to be symmetric.

practitioners. A brief overview and suggestions for practical implementation using Microsoft Excel is provided in Appendix 5.3.

5.3.2 Empirical Methodology

The first part of our empirical analysis uses a dynamic conditional correlation (DCC) model for various combinations of sectoral stock markets in the UK, US and mainland Europe to compute the time varying correlations between these markets. Extracting time-varying conditional correlations using a DCC model is computationally less burdensome, especially when estimating large systems, than using other MVGARCH models. The extracted correlations are used to identify turning points and periods of high correlations across the markets and sectors. In the second part of the analysis, we fit a BEKK-type MVGARCH model for the same combinations used in the first part. This model permits the assessment of volatility spillovers between the sectors/countries in the various combinations. We also fit various three variable BEKK MVGARCH models to look at contemporaneous spillover between all three groupings[257]. To account for the possible fat-tailedness of equity returns, we also explore a conditional multivariate t-density version of the BEKK MVGRACH model for some of our combinations. All three methodologies are outlined below.

[257] A similar approach is taken Kearney and Patton (2000) where they estimate a three variable system for currencies in the European Monetary System (EMS).

5.3.2.1 Description of time-varying correlation model

Traditionally, practitioners have calculated correlations within moving windows of a given length and used these to illustrate correlation changes. This approach is problematic because the window length selected is arbitrary and different results could be obtained with different windows. With a moving window approach, only the information in the window is used. Too short a window and the sample of data used to calculate the correlation is not representative of the true underlying process and the correlation tends to be too volatile (since it is very affected by sampling variations). Too long a window and any changes in the correlation are smoothed and so hard to detect in real-time. Smoothing short window correlations by taking a moving average produces a similar effect. Second, "ghosting" effects are observed when a large outlier enters and leaves the moving window. An exponentially weighted moving (EWMA) correlation resolves some of these issues but it also limited because the smoothing parameter must be estimated separately or fixed subjectively[258]. Engle's dynamic conditional correlation (DCC) model is free from all these problems, but comes at the cost of specifying (and estimating) a functional form for the variance-covariance process of assets.

Engle (2002a) suggests using a simple two-step procedure to extract conditional or time-varying correlations. This model is known as the Dynamic Conditional Correlation (DCC) model. The model is based on a simple two-step procedure: univariate GARCH models are fitted for each return series and the GARCH residuals are extracted and standardised. A correlation matrix is constructed and

[258] See Appendix 5.3 for a simplified primer on EWMA analysis of volatility and correlation

a GARCH process is then fitted for this correlation matrix. The model therefore allows for dynamic or time varying correlations and it is parsimonious. We adopt this method in our analysis and briefly discuss the procedure below.

The DCC model can be written as follows: k asset returns (probably filtered through a demeaning process) are normally distributed with mean zero and a time-varying covariance matrix, H_t.

$$r_t | F_{t-1} \sim N(0, H_t) \qquad \textbf{(5.6)}$$

This covariance matrix can be expressed as[259]

$$H_t = D_t R_t D_t \qquad \textbf{(5.7)}$$

where D_t is the $k \times k$ diagonal matrix of time varying standard deviations from univariate GARCH models with $\sqrt{h_{it}}$ on the i^{th} diagonal, and R_t is the time-varying correlation matrix. The simple first order univariate GARCH model is $h_{it} = \omega_i + \alpha_i r_{it-1}^2 + \beta_i h_{t-1}$ where; we note that the coefficients (may) vary across assets. This equation can be more richly specified, such as to incorporate asymmetric effects of shocks, subject to technical constraints. The residuals standardised by their conditional standard deviation are denoted $\varepsilon_{it} = r_{it} / \sqrt{h_{it}}$; $\varepsilon_{it} \sim N\left(0, R_t\right)$[260].

The dynamic correlation structure is

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[259] We hasten to note that the DCC model is simply a generalisation of the CCC. The DCC model differs only in allowing R, the correlation matrix in the CCC model, to be time varying.

[260] The conditional correlations are defined as: $\rho_{it} = \dfrac{\mathrm{E}_{t-1}\left[r_{it} r_{jt}\right]}{\sqrt{\mathrm{E}_{t-1}\left[r_{it}^2\right]\mathrm{E}_{t-1}\left[r_{jt}^2\right]}}$. Given that $\varepsilon_{it} = r_{it} / \sqrt{h_{it}}$, the conditional correlation can be written as $\rho_{ij,t} = \mathrm{E}\left[\varepsilon_{it}\varepsilon_{jt}\right]$. This is the **basic idea** of the DCC model. See Engle and Sheppard (2001) and Engle (2002a) for further details.

$$Q_t = (1-\alpha_n-\beta_n)\overline{Q} + \alpha_n(\varepsilon_{t-1}\varepsilon'_{t-1}) + \beta_n Q_{t-1} \qquad \textbf{(5.8)}$$

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \qquad \textbf{(5.9)}$$

where $\overline{Q}$ is the unconditional covariance of the standardised residuals, and

$$Q_t^* = \begin{bmatrix} \sqrt{q_{11}} & 0 & 0 & \cdots & 0 \\ 0 & \sqrt{q_{22}} & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \sqrt{q_{kk}} \end{bmatrix} \qquad \textbf{(5.10)}$$

The typical element of R_t will be of the form $\rho_{ij,t} = \dfrac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}}$. This is the conditional correlations. The dynamic correlation structure has a GARCH-like form and we have written it such that the coefficients (α_n β_n) are equal for all assets. This assumption can be relaxed and extensions to the functional form can easily be incorporated, again subject to some technical considerations. If the sum of α_n and β_n is less than unity then the correlations are mean reverting (towards the unconditional $\overline{Q}$ level). If the coefficients sum to unity then the correlations are integrated and display no mean reversion tendencies (although correlations are, of course, bounded). DCC models are estimated a simple two-step procedure as discussed above. The model is estimated by Quasi-Maximum likelihood. A fuller discussion of the theoretical properties of the procedure including the likelihood formulation for the two stage estimator is provided in Engle and Sheppard (2001). The general form likelihood function of the estimator is given as:

$$LogL\left(\theta_1\theta_2\middle|r_t\right) = -\frac{1}{2}\sum_{t=1}^{T}\left[k\log(2\pi) + \log\left(\left|H_t\right|\right) + r_t'H_t^{-1}r_t\right] \quad (5.11a)$$

Where θ_1 is the parameter set for stage one, the univariate GARCH models and θ_2 the parameter set for stage two, the dynamic correlation part. Because stage two uses the standardised version of the residuals estimated in stage one, the form of the likelihood function relies on the factorisation of the variance-covariance matrix, $H_t = D_t R_t D_t$; where $D_t = diag(\sigma_{1,t}\ldots,\sigma_{n,t})$. This means that the standardised residual can also be written as, $D_t^{-1}r_t$. With this property, the general likelihood function can be rewritten as:

$$LogL\left(\theta_1\theta_2\middle|X_t\right) = -\frac{1}{2}\sum_{t=1}^{T}\left[k\log(2\pi) + \log\left(\left|R_t\right|\right) + 2\log\left(\left|D_t\right|\right) + r_t'D_t^{-1}R_t^{-1}D_t^{-1}r_t\right]$$

(5.11b)

Engle and Sheppard (2001) decomposed the general likelihood function into a volatility part and a correlation part. The volatility part is:

$$LogL\left(\theta_1\middle|r_t\right) = -\frac{1}{2}\sum_{t=1}^{T}\left[k\log(2\pi) + \log\left(I_n\right) + 2\log\left(\left|D_t\right|\right) + r_t'D_t^{-1}I_n^{-1}D_t^{-1}r_t\right]$$

(5.11c)

where the correlation matrix is now replaced by an identity matrix. The correlation part of the general likelihood function is:

$$LogL\left(\theta_2\middle|\hat{\theta}_1, r_t\right) = -\frac{1}{2}\sum_{t=1}^{T}\left[k\log(2\pi) + \log\left(\left|R_t\right|\right) + 2\log\left(\left|D_t\right|\right) + \varepsilon_t'R_t^{-1}\varepsilon_t - \varepsilon_t'\varepsilon_t\right]$$

(5.11c)

Conditions for the consistency and asymptotic normality of the parameters is provided in Newey and McFadden (1994). See Engle and Sheppard (2001) for more details.

5.3.2.2 Description of the MVGARCH model

Assume that the multivariate mean equation in MVGARCH modelling is given as:

$$y_t = c + \varepsilon_t,\ t = 1,2,\ldots,T \qquad \textbf{(5.12a)}$$

where c is a $k \times 1$ mean vector (constant term), and ε_t is a $k \times 1$ vector of mean zero white noise terms. The variance-covariance matrix of the mean zero white noise error term can be described by the class of MVGARCH model known as the BEKK model, which was formalised in Engle and Kroner (1995). It is perhaps the most general form of the MVGARCH class of models and is very popular. The model is expressed in quadratic forms to ensure that the MVGARCH model is positive definite – no need to constrain the parameters because the quadratic form will be positive definite. The two-variable BEKK model for example is written as:

$$H_t = C'C + A_1'\varepsilon_{t-1}\varepsilon_{t-1}'A_1 + B_1'H_{t-1}B_1 \qquad \textbf{(5.12b)}$$

C, A_1 and B_1 are $k \times k$ matrices and C is upper triangular. $C'C = W > 0$ is symmetric and positive definite. The number of parameters to be estimated in this model is $2k^2 + k/2$. In the bivariate BEKK MVGARCH model we will have to estimate 12 parameters. Engle and Kroner (1995) and Engle (2002a) have shown that the BEKK model can be written in a vec representation under certain conditions; and every vec model which has a BEKK representation has a positive definite covariance matrix[261]. The two variable GARCH(1,1) BKKK model can be written as[262]:

$$\begin{pmatrix} h_{11,t} & h_{12,t} \\ h_{12,t} & h_{22,t} \end{pmatrix} = C'C + \begin{pmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{pmatrix}' \begin{pmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon_{2,t-1}^2 \end{pmatrix} \begin{pmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{pmatrix}$$
$$+ \begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix}' \begin{pmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{12,t-1} & h_{22,t-1} \end{pmatrix} \begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix}$$

(5.13a)

Following previous work in this area, see for example Karolyi (1995), Kearney and Patton (2000) and Patton (2003) we use the above model in our analysis of conditional volatility spillover analysis. Each variance in this model is affected by a covariance term and variance of the other series. Although we experimented with including ARMA terms and exogenous variables in the conditional mean and conditional variance equation of our MVGARCH model the BEKK (1, 1) turned out to be the best model for our analysis. The generality of this model is makes it capable capturing spillover effects across the sectors. To see this clearly we can rewrite (expand) the BEKK (1, 1) model in (5.13a) in a linear structure to show a variance and a covariance term respectively as:

Variance
$$\begin{aligned} h_{11} &= c_{11} + \alpha_{11}^2\varepsilon_{1,t-1}^2 + 2\alpha_{11}\alpha_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + \alpha_{21}^2\varepsilon_{2,t-1}^2 \\ &+ \beta_{11}^2 h_{11,t-1} + 2\beta_{11}\beta_{21}h_{21,t-1} + \beta_{21}^2 h_{22,t-1} \end{aligned} \qquad \textbf{(5.13b)}$$

[261] Details of the proof can be found in Engle and Kroner (1995).

[262] Both theoretically and practically, it is straightforward to fit higher-order multivariate volatility models. Examples can be found in Kearney and Patton (2000) and Tsay (2002). However, as noted before, because the number of parameter increases considerably with number of variables, higher-order volatility models are not very common in the literature.

Covariance

$$h_{21t} = c_{21} + \alpha_{11}\alpha_{22}\varepsilon_{1,t-1}^{2} + \left(\alpha_{21}\alpha_{12} + \alpha_{11}\alpha_{22}\right)\varepsilon_{1,t-1}\varepsilon_{2,t-1} + \alpha_{22}\alpha_{21}\varepsilon_{2,t-1}^{2}$$
$$+ \beta_{11}\beta_{12}h_{11,t-1} + \left(\beta_{21}\beta_{12} + \beta_{11}\beta_{22}\right)h_{21,t-1} + \beta_{22}\beta_{21}h_{22,t-1}$$

(5.13c)

It is important to note that in (5.13a) the will be two variance equation and one covariance equation. The models in 5.12b or 5.13a are estimated under the assumptions of conditional normally distributed error terms. This implies the following likelihood function

$$L(\theta) = -\frac{TN}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\left(\ln|H_t| + \varepsilon_t' H_t^{-1}\varepsilon_t\right) \qquad \textbf{(5.14)}$$

where T is the number of observations, N the number variables in the system being estimated and θ the number of parameters been estimated. We use both the simplex and Bernt, et al. (1974) (also known as BHHH) algorithms in the estimation process[263]. Alternative estimation based on multivariate conditional t distribution is also carried out for a few of the sector pairings for comparison[264]. The multivariate t-density is given as:

$$f(\varepsilon_t) = \frac{\Gamma\left[(v+k)/2\right]}{(\pi v)^{k/2}\Gamma(v/2)} \frac{|S_t|^{-1/2}}{\left[1 + \varepsilon_t' S_t^{-1}\varepsilon_t / v\right]^{(v+k)/2}} \qquad \textbf{(5.15)}$$

where $\Gamma(\cdot)$ is the gamma function. The covariance matrix of ε_t is given by $Cov(\varepsilon_t) = \frac{v}{v-2}S_t$. If the error term ε_t is assumed to follow a conditional

[263] Apart from Maximum likelihood, volatility models can also be estimated by GMM, Quasi maximum likelihood, indirect estimation and Bayesian estimation methods. See the excellent review article by Pagan (1996) for further details.

[264] For empirical application of MVGARCH models with multivariate student t density, see for example Fiorentini, et al. (2003) and Patton (2003). Kan and Zhou (2003) compare multivariate t to multivariate normal distributions in tests of asset pricing models.

multivariate student t-distribution with ν degrees of freedom and $Cov(\varepsilon_t) = H_t$, the scale matrix S_t should be chosen so that $S_t = \frac{\nu}{\nu-2}H_t$. Substituting the value for S_t in 5.15 we can derive a similar log-likelihood function as in 5.14 for MVGARCH models with conditional multivariate student t distributed errors[265].

5.4 Data

The data set for this chapter is based on the recognised global sectoral classification system used by FTSE (2002). The FTSE global classification is a benchmark for international equity market sectoral classification[266]. We study the following sectors in UK, Europe and the USA: the Insurance sector, the Pharmaceuticals sector, the Information Technology (IT) Hardware sector and the General retailers sector[267]. Two European sectoral indices were obtained – the general European sectoral indices, and the European sectoral indices excluding UK. These sectors were chosen because they capture a broad range in the overall market. The Insurance sector is perhaps the most important financial services sector. In the UK for example, forced selling of the broad market index (the FTSE 100 or FTSE All share index) can be instigated by life assurance funds (agencies), which have significant stakes in the market as whole, if for example the FTSE 100 falls below a certain threshold[268]. The pharmaceutical sector is also a very important sector given the international nature of most pharmaceutical conglomerates. The IT hardware sector is also a crucial sector in

[265] Various chapters in Engle (1995) provide additional details. See for example chapter six.
[266] Standard and Poors also have a global industrial classification system.
[267] The original intention was study the broad economic sectors as defined by the FTSE global classification system. However due to the lack of sufficient data for these groupings across the countries or region we had chose from sub-sectors for which there were sufficient data across the board.

the economy. It includes computer hardware companies, semiconductors and chip manufactures and telecommunications equipment manufactures. Together, these companies have been at the forefront of the IT revolution in the last two decades. The general retailers sectors is a cyclical services sector which include companies from discount and superstores, warehouses, e-comers retailers, department stores and other retailers. Together they capture underlying consumer demand and cyclical nature of consumer demand. Investigating volatility transmission across these sectors would reveal the effects of the sectoral nature of volatility in stock markets in the UK, US and mainland Europe and in addition, show idiosyncratic nature of UK stock market volatility from an international sectoral perspective. The dynamics of the correlation structure between these sectors is also very important. Volatility and correlation inextricably linked and correlation between financial markets tends to increase when stock market volatility is highest[269].

The data is obtained from Datastream International and all data are US dollar denominated Datastream calculated indices. We use weekly data form 4th November 1988 to 11th July 2003, which gives 767 observations[270]. We follow the standard practice in the literature to compute the continuously compounded return as the log price difference – $r_{it} = 100 \times \ln\left(p_{i,t} / p_{i,t-1}\right)$ – of each series[271]. Key descriptive statistics for the various sectors and market data is

[268] This threshold is subjective and it depends on the overall economic environment.
[269] We show, formally, the theoretical ink between correlation and volatility in the Appendix to this chapter.
[270] Weekly data are preferred in order to remove the effects of non-synchronous trading. See chapter Four for details
[271] The price data use here is the Total return indices provided by Datastream©. This data accounts for dividends and dividend reinvestments. The log transformation is necessary to make the data stationary. We also checked whether there were any cointegration relationship between

provided in Table 5.1a, Table 5.1b and Table 5.1c. Table 5.1a shows that the UK IT Hardware sector was the most volatile (volatility measured here by the unconditional standard deviation) sector of the four UK sectors. The UK IT hardware sector also displays large negative skewness whilst the skewness statistics of the other UK sector and the UK market were reasonable; close to zero. All the UK series exhibit excess kurtosis confirming the widely reported notion of excess kurtosis in financial markets. The last two statistics, the Jacque-Bera statistic and the Lilliefors statistic[272]; are a direct measure of how closely the data resembles a normal distribution. All the Jacque-Bera statistics have a p-value equal to zero at four decimal places. We therefore reject the null hypothesis that the distribution of the UK data can adequately be approximated by the normal distribution. This is confirmed by the Lilliefors statistic with p-values that rejects normality for all the series at the conventional 5% level.

Table 5.1a

the raw price data of UK sectors and the European and US sectors. None of the results suggested a significant cointegration results.

[272] The Lilliefors test of normality is an alternative to the popular Kolmogorov-Smirnov test. However, the Kolmogorov-Smirnov test requires that the cumulative density function (cdf) be predetermined. It is not accurate if cdf is estimated from the data. The Lilliefors test of normality is preferred if one wants to test the data against a normal distribution without specifying the parameters of the cdf. See D'Agostino and Stephens (1986) for further details.

	UK SECTORS				
	Insurance	Pharma	IT Hardware	Retailers	UK Market
Mean	0.0010	0.0027	0.0013	0.0016	0.0017
Median	0.0030	0.0016	0.0011	0.0017	0.0019
Maximum	0.1693	0.1397	0.4929	0.1506	0.1082
Minimum	-0.2054	-0.1118	-0.6952	-0.0931	-0.0875
Std. Dev.	0.0390	0.0336	0.0836	0.0300	0.0219
Skewness	-0.3895	0.2103	-0.5128	0.1516	0.0734
Kurtosis	5.7381	3.8696	13.9983	3.9706	4.8871
Jarque-Bera	258.9873	29.8197	3899.3918	33.0470	114.4988
Probability	0.0000	0.0000	0.0000	0.0000	0.0000
Lilliefors (D)	0.0391	0.0369	0.0846	0.0361	0.0473
Probability	0.0132	0.0243	0.0000	0.0304	0.0008
Observations	767	767	767	767	767

For the US data, Table 5.1b, the most volatile sector was the US IT hardware sector whilst the both the US IT Hardware sector and the US market index exhibit high negative skewness. All the US series display excess kurtosis and the p-values for the Jacque-Bera statistic and the Lilliefors statistics suggest the US data are not well approximated by the normal distribution.

Table 5.1b

	US SECTORS				
	Insurance	Pharma	IT Hardware	Retailers	US Market
Mean	0.0027	0.0031	0.0022	0.0028	0.0022
Median	0.0030	0.0032	0.0042	0.0044	0.0040
Maximum	0.1595	0.0983	0.1699	0.1357	0.0895
Minimum	-0.1044	-0.1220	-0.2686	-0.1230	-0.1439
Std. Dev.	0.0259	0.0289	0.0437	0.0328	0.0222
Skewness	0.3338	-0.3344	-0.5839	-0.2473	-0.6404
Kurtosis	7.2382	4.2951	6.1198	4.5792	7.2856
Jarque-Bera	588.2972	67.8965	354.6339	87.5199	639.3889
Probability	0.0000	0.0000	0.0000	0.0000	0.0000
Lilliefors (D)	0.0550	0.0399	0.0572	0.0451	0.0483
Probability	0.0000	0.0100	0.0000	0.0018	0.0005
Observations	767	767	767	767	767

Table 5.1c

	EUROPEAN SECTORS EXCLUDING UK				
	Insurance	Pharma	IT Hardware	Retailers	EXUK Market
Mean	0.0011	0.0030	0.0028	0.0019	0.0017
Median	0.0014	0.0027	0.0052	0.0031	0.0026
Maximum	0.1874	0.0967	0.2390	0.1278	0.1153
Minimum	-0.1414	-0.0804	-0.2169	-0.1218	-0.0947
Std. Dev.	0.0303	0.0237	0.0472	0.0258	0.0221
Skewness	-0.0692	-0.0927	-0.4158	-0.2915	-0.2595
Kurtosis	8.3779	3.8329	6.0797	5.8319	5.7532
Jarque-Bera	924.9009	23.2706	325.2043	267.1562	250.8585
Probability	0.0000	0.0000	0.0000	0.0000	0.0000
Lilliefors (D)	0.0694	0.0372	0.0816	0.0509	0.0559
Probability	0.0000	0.0224	0.0000	0.0002	0.0000
Observations	767	767	767	767	767

Table 5.1c reports data for the European sectors excluding the UK. This data was chosen because it does not include UK companies in the indices. This was necessary because the objective of our analysis is to assess the effects of purely European sectoral equity market volatility on UK stock market volatility. The most volatile European sector is the IT Hardware sector and it also exhibits relatively large negative skewness although, it is far less skewed than UK or US IT hardware sector. Consistent with the other data, the European market also displays excess kurtosis and the distribution of the data is not close to the normal distribution as the p-values of both the Jacque-Bera statistic and the Lilliefors statistic suggest a rejection of normality at the conventional 5% level.

5.5 Empirical Results

5.51 DCC Time-varying correlations Results

The DCC model is estimated in two stages. In stage one, univariate GARCH models are estimated for each series. In stage two, the estimated residuals from stage one are standardised by dividing them by their conditional standard deviation and a GARCH-type correlation model is estimated for the standardised residuals. The DCC implemented in this chapter uses an AR(1)-GARCH(1, 1) model in stage one[273]. It is assumed that returns follow a simple AR(1) dependency structure and the conditional volatility follows a GARCH (1, 1) process, which means that the volatility at time t is dependent on shocks and the volatility at time $t-1$. This simple and parsimonious structure adequately captures the volatility clustering in our data[274]. The AR(1)-GARCH(1, 1) model comprise the following mean and variance equations:

Mean equation $$r_{i,t} = \phi_0 + \phi_1 r_{i,t-1} + \sigma_t w_t \quad \textbf{(5.16)}$$

Variance equation $$\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + \alpha\varepsilon_{t-1}^2 \quad \textbf{(5.17)}$$

$\varepsilon_t = \sigma_t w_t$; $w_t \sim IID(0,1)$;

In stage two, the model in (5.8), $Q_t = \left(1-\alpha_n - \beta_n\right)\bar{Q} + \alpha_n\left(\varepsilon_{t-1}\varepsilon_{t-1}'\right) + \beta_n Q_{t-1}$, which has already been described, is fitted for the correlation part of the analysis.

Four sets of bilateral DCC are estimated in this chapter. The first model estimates bilateral correlations between the UK stock market and the US stock market (which includes the US sectors and US stock market). There are four sectors plus the two market indices. We are therefore estimating a six-variable DCC model. This second model estimates bilateral correlations between UK sectoral stock markets and US sectoral stock markets. This inter-sectoral correlation analysis

[273] We follow Antoniou, et al. (2003) who employed an AR(1) filtration process in their MVGARCH model for European equities and futures markets.

[274] Although a complicated structure including asymmetric models, could be implemented, evidence, for example Akgiray (1989) found that the simple GARCH(1, 1) model fits the data 'very satisfactorily' and provide 'superior' forecasts; Hansen and Lunde (2001), suggests that

requires an eight-variable DCC model. In both models only the relevant UK bilateral correlations are extracted.

The third DCC model estimates the time-varying correlations between the UK stock market and the European sectoral stock market, which excludes UK data. There are four sectors plus the two market indices; which requires a six-variable DCC model. The fourth DCC model, an eight-variable DCC model, is estimated for the time-varying bilateral correlations between the UK sectoral stock markets and the European sectoral stock markets. Once again, only the relevant UK bilateral correlations are extracted. The estimation results and selected correlation charts are provided next.

5.51.1 Time-varying correlations between the UK and US stock markets

The equally weighted average bilateral DCC between the UK stock market and the US sectoral markets is given in Figure 5.51a. Figure 5.51b displays the average bilateral DCC between the UK stock market and the US stock market. The estimation results are given in Table 5.51a. The individual bilateral DCCs are given in Figure A5.11 in appendix 5.1[275]. For inter-sectoral correlations, the average bilateral correlations between UK sectoral stock markets and US sectoral stock market is given in Figure 5.51c. The estimation results are given in Table 5.51b. Additional correlations charts are given in Appendix 5.1a. These include all the pairwise correlation for the UK stock market and sectoral stock market.

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complicated models do not necessarily provide a superior forecast to the simple GARCH (1,1) model. Poon and Granger (2003) review volatility forecasting models in financial markets.

[275] Also included in Appendix 5.1a are the full estimation results with the likelihood function value, convergence information and post GARCH estimation diagnostic results.

The results from stage one (Table 5.51a) of the DCC estimation suggests that the AR(1) GARCH(1,1) model was indeed an adequate univariate GARCH model for each of the series. Post estimation diagnostics of the autocorrelation function (ACF) of the residual from each univariate GARCH model indicate that there were no serial correlation in both the standardised residuals and the squared standardised residuals. We report Ljung-Box Q-Statistics for the standardised and squared standardised residuals in the appendix[276]. It is important for DCC modelling that the univariate GARCH model fitted for each series in stage one to be appropriately robust otherwise; results from the time-varying correlation part in stage two would be misleading.

Figure 5.51a shows that average correlation between the UK benchmark index and the four selected US sectors increased substantially after 1997. In general, average correlations have risen since mid-1990s and by around August 2002 have reached their sample period highs. Figure 5.51a also shows some interesting features of the model. It reveals sufficient variation in the correlation between the UK stock market and the US sectors sectoral stock markets, which would most probably not have been revealed by standard equally weighted moving average correlation models. Limited experimentation with extended functional forms for the variance processes (equation (5.17)), suggests that the trends observed in the correlations are robust although the magnitudes of the oscillation about the trends depend on the exact functional form assumed. It would be interesting to explore this in future research work.

Figure 5.51a Average DCC Time-varying correlations between the UK stock market and US sectoral stock markets

Figure 5.51b DCC Time-varying correlations between the UK stock market and the US stock market

The average correlation between the US sectors and the UK stock market loosely mirrors the correlation between the US stock market and the UK stock market.

[276] Due to space restriction we only report one post estimation diagnostics result. One post estimation diagnostic result takes about four pages. If we were to report all of them this will take

There is however more variation in the average sectoral correlation than between the market indices. This suggests that sectoral market correlations, rather than average market to market correlation, may be driving the overall UK market correlation with the US market; suggesting perhaps that the selected US sectors are more important in understanding the variations in the UK stock markets over the sample period used.

The estimated DCC coefficients (bottom of Table 5.51a) summed to 0.98. The estimated GARCH parameter of the correlation part of the DCC model is 0.96 and the ARCH parameter is 0.02 suggesting that the correlation structure is highly persistent although it can still be described as a mean reverting correlation processes. All the univariate GARCH models in stage are all reasonably well specified with significant ARCH and GARCH parameter. Overall, we feel reasonably satisfied that our DCC model is correctly specified and captures the time variation of the correlation structure between the sectors.

Table 5.51a Six-variable DCC estimation result for UK market, US sectors and US stock market

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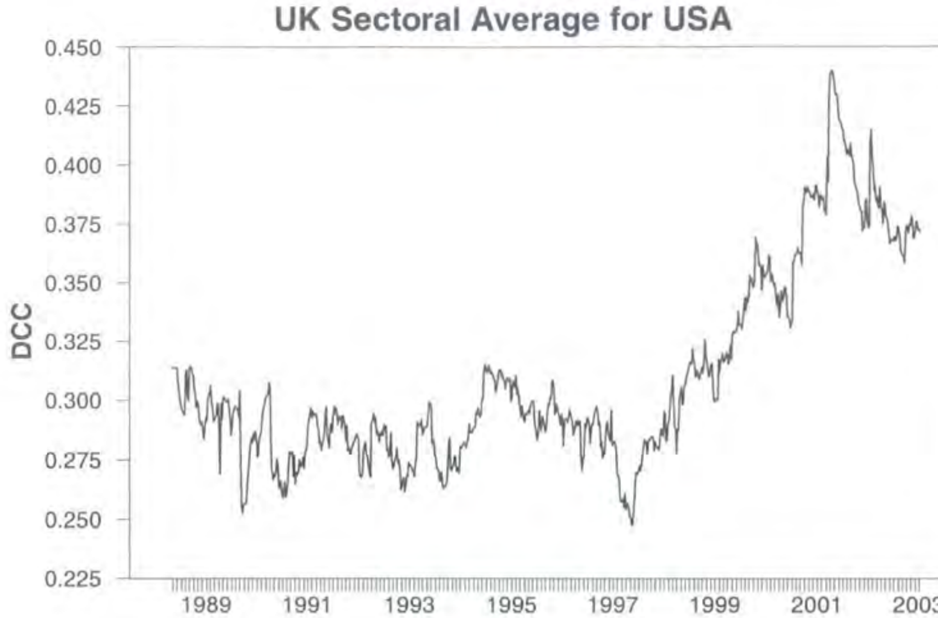
about nineteen pages.

STAGE 1 UNIVARIATE GARCH PART				
Variable	Coeff	Std Error	T-Stat	Signif
1. PHI0(1)	0.2071	0.0762	2.7188	0.0066
2. PHI0(2)	0.3664	0.0817	4.4839	0.0000
3. PHI0(3)	0.4400	0.0986	4.4617	0.0000
4. PHI0(4)	0.3172	0.1107	2.8654	0.0042
5. PHI0(5)	0.3224	0.0997	3.2330	0.0012
6. PHI0(6)	0.3100	0.0633	4.9003	0.0000
7. PHI1(1)	-0.0244	0.0424	-0.5771	0.5639
8. PHI1(2)	-0.0479	0.0414	-1.1563	0.2475
9. PHI1(3)	-0.1082	0.0363	-2.9791	0.0029
10. PHI1(4)	-0.0429	0.0378	-1.1346	0.2565
11. PHI1(5)	-0.0524	0.0356	-1.4742	0.1404
12. PHI1(6)	-0.1111	0.0343	-3.2416	0.0012
13. OMEGA(1)	1.3997	0.0767	18.2594	0.0000
14. OMEGA(2)	0.3238	0.0380	8.5170	0.0000
15. OMEGA(3)	0.1217	0.0106	11.5091	0.0000
16. OMEGA(4)	0.1324	0.0236	5.5991	0.0000
17. OMEGA(5)	0.1413	0.0257	5.4950	0.0000
18. OMEGA(6)	0.0131	0.0045	2.8834	0.0039
19. ALPHA(1)	0.1124	0.0154	7.3186	0.0000
20. ALPHA(2)	0.1679	0.0089	18.9609	0.0000
21. ALPHA(3)	0.0351	0.0012	28.8198	0.0000
22. ALPHA(4)	0.0445	0.0021	21.4819	0.0000
23. ALPHA(5)	0.0634	0.0034	18.7681	0.0000
24. ALPHA(6)	0.0436	0.0017	25.6753	0.0000
25. BETA(1)	0.5962	0.0163	36.6164	0.0000
26. BETA(2)	0.7904	0.0074	106.1944	0.0000
27. BETA(3)	0.9513	0.0011	866.0665	0.0000
28. BETA(4)	0.9499	0.0020	476.2770	0.0000
29. BETA(5)	0.9240	0.0029	315.1717	0.0000
30. BETA(6)	0.9559	0.0015	644.7387	0.0000
STAGE 2 CORRELATION PART				
Variable	Coeff	Std Error	T-Stat	Signif
1. ALPHA_C	0.0214	0.0011	20.2445	0.0000
2. BETA_C	0.9633	0.0021	449.4897	0.0000

Figure 5.51c Inter-sectoral DCC Time-varying correlations between the UK sectoral stock market and the US sectoral stock market – The UK sectoral Average for US



An eight variable inter-sectoral DCC model for UK and US was also estimated to examine the cross-sectoral relationships between the two markets. The estimated DCC GARCH and ARCH coefficients are 0.97 and 0.01 (bottom of Table 5.51b) suggesting a persistent variation in correlation levels. The average inter-sectoral correlation for UK sectors is given in Figure 5.51c.

The result indicates that the variation in inter-sectoral correlation (the eight-variable model) is slightly more pronounced than that of the correlation between the UK market and the US sectors and the US market (the six-variable model)[277]. This is due perhaps to the significant increase in inter-sectoral bilateral correlations after 1997 (Figure 5.51c). This increase in bilateral correlation over time is also indicative of the interdependence (hence capital market integration) between the UK stock market and the US stock market and, more importantly,

[277] Although there is only one-percentage point difference between the persistence coefficients of both models, this could still be very important. Consider for example a simple exponential smoothing model; a one-percentage point difference in the smoothing parameter indicates a higher level of smoothing which could be noticeable in any graphs produced.

between the UK market and the selected US sectoral markets. Next we examine the evidence for the bilateral correlations between Europe and UK to enable possible comparisons.

Table 5.51b eight-variable DCC estimation result for time-varying correlations between the UK market sectoral stock markets and the US sectoral stock markets

STAGE 1 UNIVARIATE GARCH PART				
Variable	**Coeff**	**Std Error**	**T-Stat**	**Signif**
1. PHI0(1)	0.2193	0.1185	1.8508	0.0642
2. PHI0(2)	0.3873	0.1115	3.4721	0.0005
3. PHI0(3)	0.6248	0.2217	2.8180	0.0048
4. PHI0(4)	0.1791	0.0976	1.8341	0.0666
5. PHI0(5)	0.3667	0.0763	4.8084	0.0000
6. PHI0(6)	0.4420	0.0797	5.5475	0.0000
7. PHI0(7)	0.3156	0.1100	2.8684	0.0041
8. PHI0(8)	0.3871	0.0968	3.9983	0.0001
9. PHI1(1)	-0.0272	0.0320	-0.8510	0.3948
10. PHI1(2)	-0.0756	0.0361	-2.0965	0.0360
11. PHI1(3)	0.0836	0.0366	2.2814	0.0225
12. PHI1(4)	-0.0380	0.0401	-0.9488	0.3427
13. PHI1(5)	-0.0459	0.0387	-1.1863	0.2355
14. PHI1(6)	-0.1080	0.0452	-2.3883	0.0169
15. PHI1(7)	-0.0472	0.0443	-1.0654	0.2867
16. PHI1(8)	-0.0481	0.0353	-1.3596	0.1739
17. OMEGA(1)	3.2443	1.8513	1.7524	0.0797
18. OMEGA(2)	0.3822	0.1373	2.7844	0.0054
19. OMEGA(3)	0.7908	0.3960	1.9969	0.0458
20. OMEGA(4)	2.3654	1.6593	1.4255	0.1540
21. OMEGA(5)	0.3533	0.1951	1.8106	0.0702
22. OMEGA(6)	0.1728	0.1740	0.9931	0.3207
23. OMEGA(7)	0.0624	0.0477	1.3081	0.1908
24. OMEGA(8)	0.6239	0.4196	1.4869	0.1371
25. ALPHA(1)	0.1657	0.0721	2.2977	0.0216
26. ALPHA(2)	0.0328	0.0127	2.5819	0.0098
27. ALPHA(3)	0.0311	0.0107	2.9141	0.0036
28. ALPHA(4)	0.1205	0.0478	2.5186	0.0118
29. ALPHA(5)	0.1789	0.0496	3.6063	0.0003
30. ALPHA(6)	0.0490	0.0205	2.3907	0.0168
31. ALPHA(7)	0.0448	0.0117	3.8260	0.0001
32. ALPHA(8)	0.1468	0.0472	3.1076	0.0019
33. BETA(1)	0.6197	0.1677	3.6946	0.0002
34. BETA(2)	0.9352	0.0177	52.7344	0.0000
35. BETA(3)	0.9610	0.0110	87.4063	0.0000
36. BETA(4)	0.6193	0.2148	2.8840	0.0039
37. BETA(5)	0.7751	0.0677	11.4460	0.0000
38. BETA(6)	0.9312	0.0379	24.5825	0.0000
39. BETA(7)	0.9541	0.0110	86.9960	0.0000
40. BETA(8)	0.7953	0.0829	9.5982	0.0000
STAGE 2 CORRELATION PART				
Variable	**Coeff**	**Std Error**	**T-Stat**	**Signif**
1. ALPHA_C	0.0105	0.0015	7.0605	0.0000
2. BETA_C	0.9718	0.0041	237.6615	0.0000

5.51.2 Time-varying correlations between the European and UK stock markets

The average bilateral DCC between the UK stock market and European sectoral markets is displayed in Figure 5.51d. Figure 5.51e gives the average bilateral DCC between the UK stock market and the European stock market index. Estimation results are given in Table 5.51c. The individual bilateral DCCs are given in Figure A5.13 in appendix 5.1a. For inter-sectoral correlations, the average bilateral correlations between UK sectoral stock markets and the European sectoral stock market is given in Figure 5.51f and estimation results are given in Table 5.51d. UK pairwise inter-sectoral correlations with Europe are given in Appendix 5.1a.

The estimated coefficients for the six-variable DCC between the UK stock market and European sectoral markets and the European stock index are 0.97 (GARCH) and 0.02 (ARCH) [Table 5.1c]. Diagnostic tests (not reported) of the standardised and squared standardised residuals from the univariate GARCH models estimated in stage one were reasonable. The variation (ARCH plus GARCH parameter summed to 0.99) in the bilateral correlations between the UK stock market and the European stock market is slightly higher than for between the UK and the US stock market (ARCH plus GARCH parameter summed to 0.98); for this six-variable DCC. Also, the average bilateral correlation between the UK stock market and the European sectors (Figure 5.51d) seems to be higher than the bilateral correlations between the UK stock market and US sectoral stock markets (Figure 5.51a). This suggests that the level of interdependence between the broad UK market index and European sectors is much stronger. This has obvious implications for international diversifications for the UK investor. High bilateral correlation might suggest evidence of exposures to common shocks. In other words, there is perhaps strong commonality between the UK market index and sectoral stock markets in Europe on the basis of our selected sectors. Remembering of course that the European sectors studied does not include any UK firms in the sectoral composition.

Figure 5.51d Average DCC Time-varying correlations between the UK stock market and European sectoral stock markets

The average bilateral DCC between the UK stock market index and the European stock market index (Figure 5.51e) is also higher than the average UK bilateral DCC with the US stock market index (Figure 5.51b) especially after 1997. Together, these two results have significant implications for international portfolio diversification. On the basis of the bilateral DCC structure it appears the UK investor stands to obtain higher diversification gains if their portfolio or asset allocation strategy is geared towards the US stock market and in particular, the sectors selected here. We acknowledge that asset allocation decision is part of wider investment strategy and other factors are likely to be taken into consideration before an investor builds up exposures in a particular market. Nevertheless, It appears the process of European economic and financial integration in the late 1980's and the 1990's have been that major European stock markets have become closely linked despite the fact that the UK for example is still outside the euro currency area.

Figure 5.51e DCC Time-varying correlations between the UK stock market and the European stock market

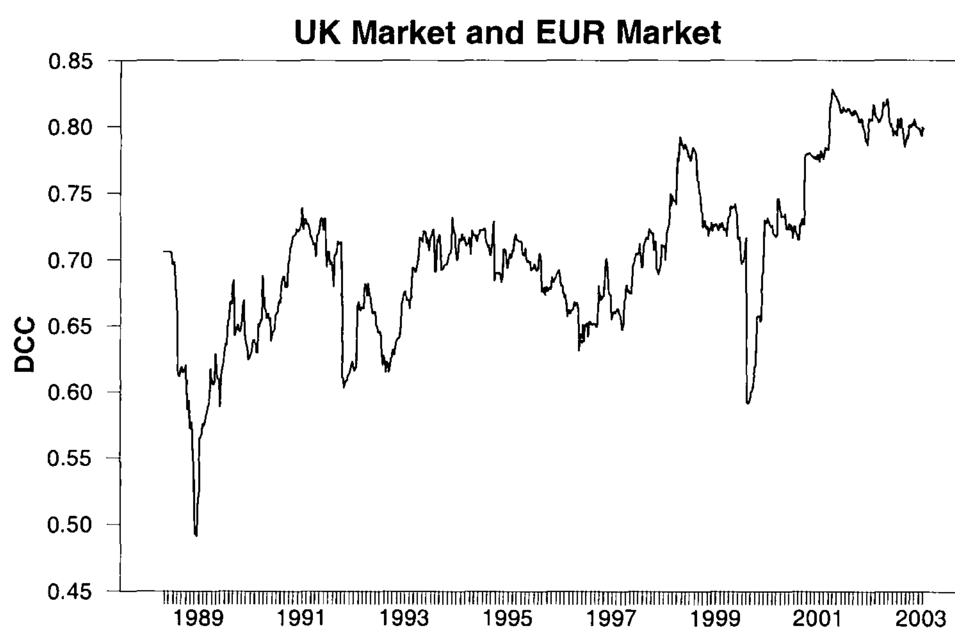


Table 5.51c six-variable DCC estimation result for UK market, European sectors and European stock market Index

STAGE 1 UNIVARIATE GARCH PART				
Variable	Coeff	Std Error	T-Stat	Signif
1. PHI0(1)	0.1975	0.0648	3.0461	0.0023
2. PHI0(2)	0.2251	0.1028	2.1899	0.0285
3. PHI0(3)	0.3467	0.0704	4.9229	0.0000
4. PHI0(4)	0.4882	0.1211	4.0307	0.0001
5. PHI0(5)	0.2645	0.1027	2.5768	0.0100
6. PHI0(6)	0.2666	0.0470	5.6764	0.0000
7. PHI1(1)	-0.0226	0.0397	-0.5696	0.5689
8. PHI1(2)	0.0558	0.0428	1.3019	0.1930
9. PHI1(3)	-0.0290	0.0526	-0.5507	0.5818
10. PHI1(4)	-0.0022	0.0455	-0.0478	0.9619
11. PHI1(5)	0.0374	0.0389	0.9612	0.3364
12. PHI1(6)	0.0002	0.0529	0.0030	0.9976
13. OMEGA(1)	1.3584	0.3760	3.6127	0.0003
14. OMEGA(2)	0.5695	0.2779	2.0488	0.0405
15. OMEGA(3)	0.8388	1.9886	0.4218	0.6732
16. OMEGA(4)	0.2105	0.1206	1.7459	0.0808
17. OMEGA(5)	0.5579	0.7468	0.7471	0.4550
18. OMEGA(6)	0.2591	0.1722	1.5050	0.1323
19. ALPHA(1)	0.1114	0.0419	2.6557	0.0079
20. ALPHA(2)	0.1865	0.0555	3.3576	0.0008
21. ALPHA(3)	0.0740	0.0789	0.9373	0.3486
22. ALPHA(4)	0.0934	0.0276	3.3844	0.0007
23. ALPHA(5)	0.1129	0.0915	1.2338	0.2173
24. ALPHA(6)	0.1415	0.0568	2.4898	0.0128
25. BETA(1)	0.6057	0.0778	7.7881	0.0000
26. BETA(2)	0.7568	0.0724	10.4507	0.0000
27. BETA(3)	0.7777	0.4254	1.8280	0.0675
28. BETA(4)	0.9008	0.0273	32.9678	0.0000
29. BETA(5)	0.8050	0.1938	4.1533	0.0000
30. BETA(6)	0.8099	0.0755	10.7206	0.0000
STAGE 2 CORRELATION PART				
Variable	Coeff	Std Error	T-Stat	Signif
1. ALPHA_C	0.0171	0.0011	15.8902	0.0000
2. BETA_C	0.9673	0.0026	367.2801	0.0000

We also studied inter-sectoral relationships between the selected UK and European sectoral stock markets. As previously, for this analysis we utilise the eight-variable DCC model. The results indicates that the sectoral variation in the UK bilateral correlation with Europe is very high (ARCH parameter = 0.01; GARCH parameter = 0.98) suggesting the UK inter-sectoral correlation with

Europe is highly persistent but mean reverting. Consistent with the six-variable DCC, the average UK inter-sectoral correlation for Europe is higher that the average UK inter-sectoral correlation for the US.

Overall, the DCC evidence indicates that recent bilateral correlations between the UK and Europe, especially after 1997 are higher than those with the US. Perhaps these results should not be entirely surprising. Anecdotal evidence suggests that the UK does a greater proportion of it trade with Europe than the US.

Figure 5.51f Inter-sectoral DCC Time-varying correlations between the UK sectoral stock market and the European sectoral stock market – The UK sectoral Average for Europe

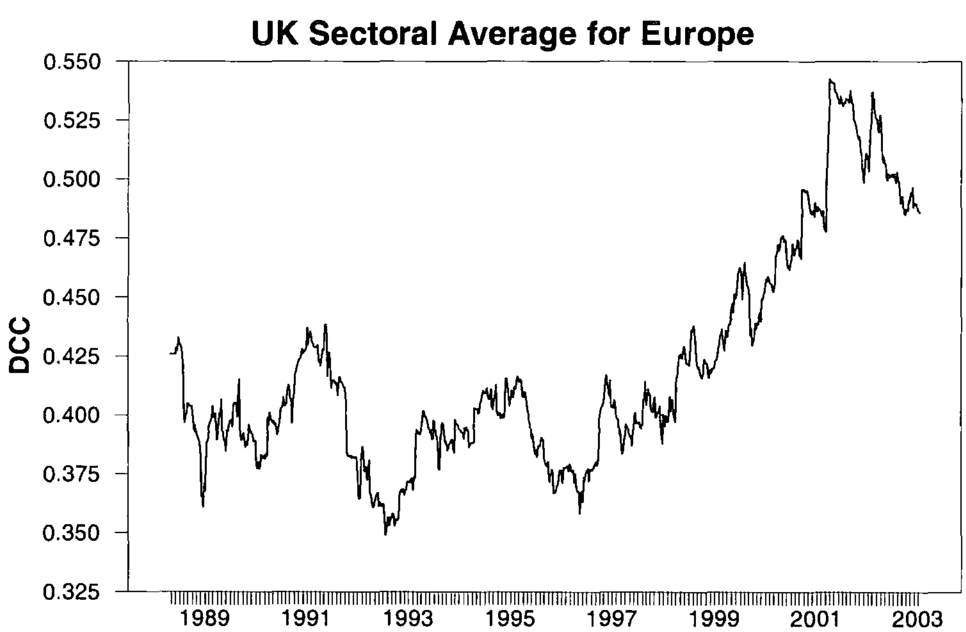


Table 5.51d eight-variable DCC estimation result for time-varying correlations between the UK market sectoral stock markets and the European sectoral stock markets

STAGE 1 UNIVARIATE GARCH PART				
Variable	Coeff	Std Error	T-Stat	Signif
1. PHI0(1)	0.2193	0.1295	1.6942	0.0902
2. PHI0(2)	0.3873	0.1091	3.5513	0.0004
3. PHI0(3)	0.6248	0.2918	2.1413	0.0323
4. PHI0(4)	0.1791	0.1001	1.7899	0.0735
5. PHI0(5)	0.2321	0.0881	2.6354	0.0084
6. PHI0(6)	0.3521	0.0810	4.3483	0.0000
7. PHI0(7)	0.4747	0.1101	4.3106	0.0000
8. PHI0(8)	0.2617	0.0933	2.8059	0.0050
9. PHI1(1)	-0.0272	0.0421	-0.6465	0.5180
10. PHI1(2)	-0.0756	0.0346	-2.1874	0.0287
11. PHI1(3)	0.0836	0.0366	2.2841	0.0224
12. PHI1(4)	-0.0380	0.0375	-1.0148	0.3102
13. PHI1(5)	0.0570	0.0382	1.4936	0.1353
14. PHI1(6)	-0.0298	0.0369	-0.8056	0.4205
15. PHI1(7)	-0.0095	0.0363	-0.2613	0.7939
16. PHI1(8)	0.0371	0.0377	0.9831	0.3255
17. OMEGA(1)	3.2443	1.7556	1.8479	0.0646
18. OMEGA(2)	0.3822	0.1159	3.2991	0.0010
19. OMEGA(3)	0.7908	0.4029	1.9628	0.0497
20. OMEGA(4)	2.3654	1.4317	1.6521	0.0985
21. OMEGA(5)	0.5949	0.2418	2.4601	0.0139
22. OMEGA(6)	0.6078	1.2579	0.4832	0.6290
23. OMEGA(7)	0.3778	0.1106	3.4150	0.0006
24. OMEGA(8)	0.6702	0.4236	1.5819	0.1137
25. ALPHA(1)	0.1657	0.0636	2.6043	0.0092
26. ALPHA(2)	0.0328	0.0099	3.3062	0.0009
27. ALPHA(3)	0.0311	0.0094	3.3115	0.0009
28. ALPHA(4)	0.1205	0.0419	2.8720	0.0041
29. ALPHA(5)	0.1926	0.0466	4.1318	0.0000
30. ALPHA(6)	0.0651	0.0575	1.1322	0.2576
31. ALPHA(7)	0.1069	0.0243	4.4064	0.0000
32. ALPHA(8)	0.1227	0.0548	2.2376	0.0252
33. BETA(1)	0.6197	0.1610	3.8483	0.0001
34. BETA(2)	0.9352	0.0146	63.9290	0.0000
35. BETA(3)	0.9610	0.0108	89.2532	0.0000
36. BETA(4)	0.6193	0.1844	3.3592	0.0008
37. BETA(5)	0.7480	0.0602	12.4177	0.0000
38. BETA(6)	0.8278	0.2799	2.9573	0.0031
39. BETA(7)	0.8785	0.0239	36.7572	0.0000
40. BETA(8)	0.7786	0.1107	7.0306	0.0000
STAGE 2 CORRELATION PART				
Variable	Coeff	Std Error	T-Stat	Signif
1. ALPHA_C	0.0093	0.0006	14.8956	0.0000
2. BETA_C	0.9764	0.0021	466.4350	0.0000

5.5.2 Volatility Transmission Results

In the light of the results presented in the previous section showing that DCCs vary considerably over time, the paper proceeds to analyse the volatility transmission mechanism over the same sample period and across the same markets and sectors[278]. Before reporting the volatility transmission results it is appropriate to comment on the levels of volatility in the UK stock market in relation the preceding analysis of DCC time varying correlations[279]. This is particularly important because previous research suggests that correlation between financial markets is highest during highly volatile bear markets[280]. The AR(1)-GARCH (1, 1) model, described in 5.16 and 5.17, is estimated for the UK stock market, US stock market and the European stock market. The extracted conditional standard deviation is given in Figure 5.52a, Figure 5.52b and Figure 5.52c. The results confirm anecdotal evidence in financial markets that over the last decade, the most volatile periods was at the height of the bear market between the end of 2001 and during most of 2002. The recession of the early 1990's also witnessed highly volatile markets.

The results for the DCC bilateral correlation are slightly mixed. Although the evidence suggest that correlation was very high during the recent bear market following the bursting of the technology bubble in 1999, the picture from the early 1990's recession are mixed. The average UK sectoral correlation with the

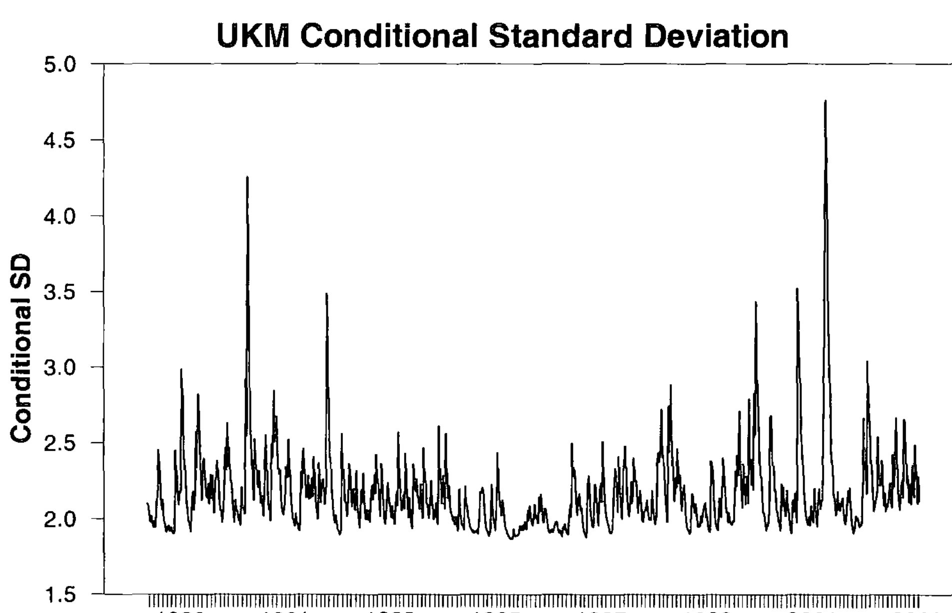
[278] Higher capital market integration is synonymous with increased time-varying correlations, as well as more volatility spillovers, between markets and sectors. This is the link between the correlation and volatility transmission models.

[279] The theoretical links between conditional correlations and conditional volatilities is given in appendix 5.2

US sectors shows no dramatic correlation behaviour between 1991 and 1993 whilst the UK sectoral average with European sectors appear to show a significant but gradual drop in correlation towards the middle of 1993.

In most cases bilateral correlations were very high between 1991 and 1992 but fell dramatically towards the end of 1992 suggesting perhaps that 1993 was a significant turning point in the UK correlation cycle, see the graphs in appendix A5.1. This suggests that at the height of a recessionary period bilateral correlations were also very high but fell sharply around the beginning of the recovery period. Our results therefore confirms the stylised facts reported in Longin and Solnik (2001), Ang and Chen (2002) and Ang and Bekaert (2002) especially for very recent stock market behaviour.

Figure 5.52a UK stock market conditional volatility



[280] See for example Longin and Solnik (1995), Longin and Solnik (2001) , Ang and Chen (2002) and Ang and Bekaert (2002).

Figure 5.52b US stock market conditional volatility

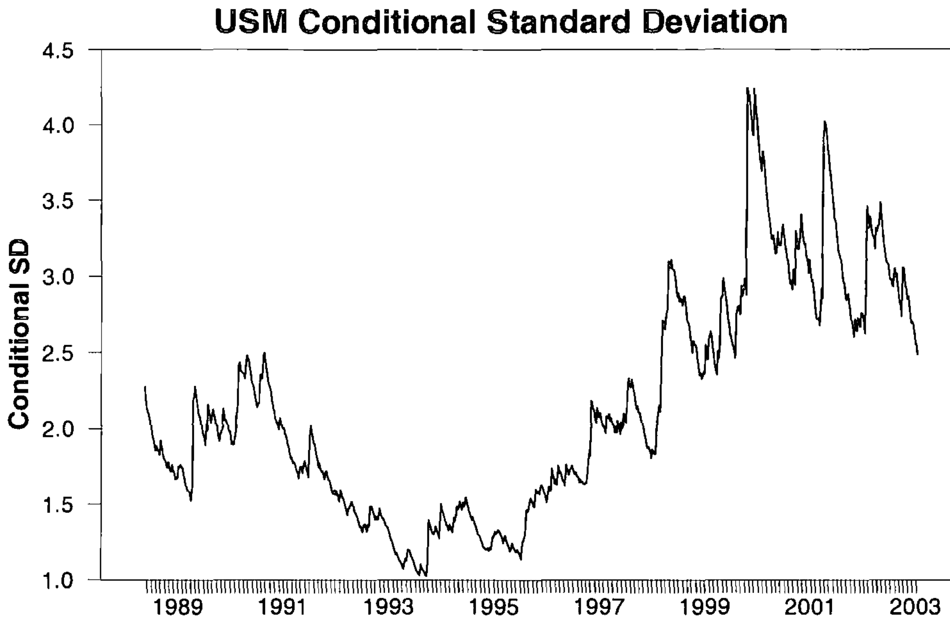
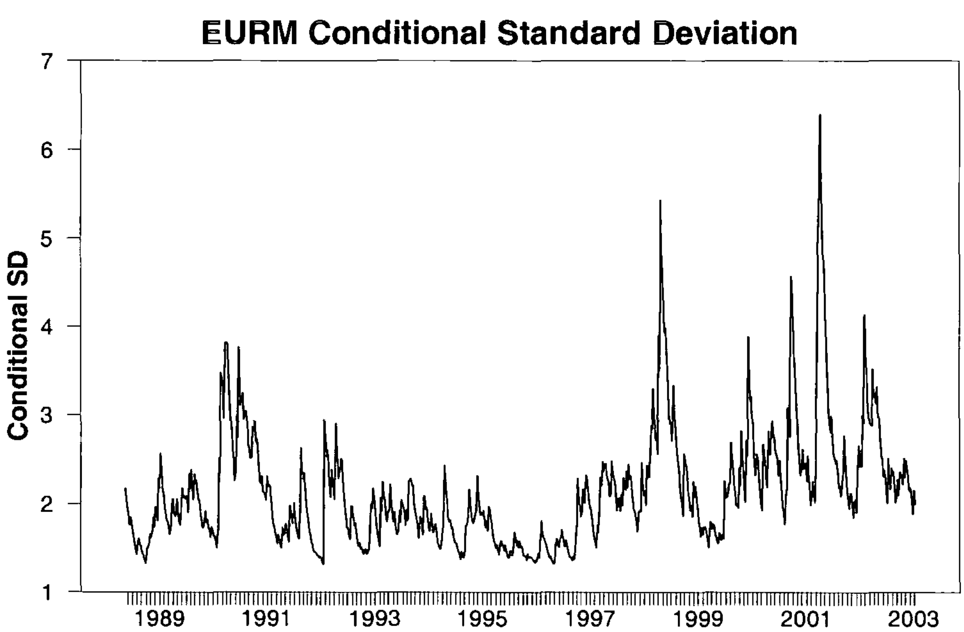


Figure 5.52c European stock market conditional volatility



To assess the extent of volatility transmission between the UK stock market and the US and European stock markets an MVGARCH model of various bivariate and trivariate combinations of the sectoral and market data in the dataset is used.

As noted earlier a number of studies in the academic literature have employed MVGARCH-type models to study volatility spillovers between financial markets. These include, Chan, et al. (1992), Lin, et al. (1994), Antoniou and Holmes (1995), Koutmos and Booth (1995), Karolyi (1995), Kearney and Patton (2000), Ng (2000) and Antoniou, et al. (2003). We follow specifically, Karolyi (1995), Kearney and Patton (2000) and Patton (2003)

The Engle and Kroner (1995) general BEKK-MVGARH model described in section 5.32.2 is used to analyse volatility transmission in this chapter. This model is a very general model is perhaps the best MVGARCH time-varying correlation model that could be used to assess conditional volatility transmission, Patton (2003). However, depending on the econometric software used and the nature of the script or code, there could be considerable convergence and optimisation problems. For this chapter a number of alternative econometric software packages have been used to estimate the BEKK-MVGARCH model giving very mixed results.

The following modelling approach is therefore adopted. For each of the bivariate and trivariate combination of the indices, a BEKK-MVGARCH model is estimated. If the BEKK model fails to converge after a number of attempts, an alternative MVGARCH model that assures non-negativeness of the variance-covariance matrix is estimated[281]. For this alternative estimation, the *vector-diagonal* model, a variant of the *matrix-diagonal* model suggest by Ding 1994 [see Zivot and Wang (2003)] and Bollerslev, et al. (1994) is used. In the *matrix-*

[281] Even when a model converges, if the post estimation diagnostics do not verify the validity of the model, an alternative MVGARCH model is estimated

diagonal model, the Cholesky factors of the coefficient matrices are estimated. The *matrix diagonal* model can be written as:

$$\Sigma_t = A_0 A_0' + \sum_{i=1}^{p} \left(A_i A_i' \right) \otimes \left(\varepsilon_{t-i} \varepsilon_{t-i}' \right) + \sum_{j=1}^{q} \left(B_i B_i' \right) \otimes \Sigma_{t-j}$$

where A_0, A_i (for $i = 1, \cdots, p$) and B_j(for $j = 1, \ldots, q$) are all lower triangular matrices. To get the *vector-diagonal,* the *matrix-diagonal* model is simplified further by restricting the A_i and B_j coefficient matrices to be vectors, which give the following conditional covariance equation:

$$\Sigma_t = A_0 A_0' + \sum_{i=1}^{p} \left(a_i a_i' \right) \otimes \left(\varepsilon_{t-i} \varepsilon_{t-i}' \right) + \sum_{j=1}^{q} \left(b_i b_i' \right) \otimes \Sigma_{t-j} \quad \textbf{(5.18)}$$

where a_i and b_i are $k \times 1$ vectors. This is the alternative model that is estimated when a bivariate or trivariate combination of the sector and market does not have a valid BEKK-MVGARCH model.

The intuition, estimations procedures and general description of the *vector-diagonal* model follows the same description as the BEKK-MVGARCH model. In fact, Bollerslev, et al. (1994), Kroner and Ng (1998) and Engle (2002a) have shown that *vector-diagonal* and *matrix diagonal* models are special case of the BEKK-MVGARCH model.

To understand our volatility spillover result and the estimation undertaken, we have provided summary tables (Appendix 5.1b) of the MVGARCH models estimated for the various combinations including whether or not convergence was reached in the nonlinear optimization process. A total of 46 bivariate and trivariate MVGARCH models with multivariate conditional normal density were estimated. We also experimented with a number of MVGARCH models with multivariate student t density but these did not change the summary of the validity of the of the various MVGARCH models given in Appendix 5.1b although, naturally they provided a slightly better fit than their multivariate normal counterpart[282]. Due to word restriction only one result from a student t BEKK-MVGARCH model is also provided.

5.5.2.1 Volatility Transmission Results for spillovers from selected US sectors into the UK stock market.

Before discussing our spillover results, it is important to stress that although we have used the general first order BEKK-MVGARCH model here; other specification of the MVGARCH model especially those that utilise both sophisticated mean equation and conditional covariance equation parameterisation including for example, a vector auto regression (VAR)-type MVGARCH model, Karolyi (1995) and Antoniou, et al. (2003) or the asymmetric dynamic covariance (ADC) model, Kroner and Ng (1998) and Ng (2000) could provide a similar scenario to capture spillover effects between the variables studied. However, since we would like to focus only on the second moments to characterise spillovers between the respective sectors, we follow Kearney and Patton (2000) and Patton (2003) who use the general BEKK-MVGARCH model for a similar purpose. The BEKK-MVGARCH model being a symmetric and positive definite time-varying correlation MVGARCH model makes it a better alternative to for example, the standard CCC MVGARCH

[282] Recently, Comte and Lieberman (2003) has proved asymptotic normality for the quasi-MLE estimator of multivariate GARCH models. It is therefore reasonable to assume conditional

model, which was used in studies such as Koutmos and Booth (1995) or Theodossiou, et al. (1997).

Table 5.52.1a: Volatility transmission between US insurance sector and the UK stock market using the BEKK-MVGARCH model. Variable ordered as USINS and UKM respectively

Estimated Coefficients				
	Value	Std.Error	t value	Pr(>|t|)
C(1)	0.0032	0.0008	4.0860	0.0000
C(2)	0.0025	0.0008	3.1920	0.0007
A(1, 1)	0.0067	0.0010	6.6040	0.0000
A(2, 1)	0.0043	0.0015	2.7940	0.0027
A(2, 2)	0.0017	0.0015	1.1630	0.1227
ARCH(1; 1, 1)	0.3801	0.0402	9.4580	0.0000
ARCH(1; 2, 1)	0.0748	0.0296	2.5230	0.0059
ARCH(1; 1, 2)	0.1098	0.0316	3.4710	0.0003
ARCH(1; 2, 2)	0.1865	0.0258	7.2300	0.0000
GARCH(1; 1, 1)	0.8790	0.0200	43.9950	0.0000
GARCH(1; 2, 1)	-0.0459	0.0127	-3.6260	0.0002
GARCH(1; 1, 2)	-0.0295	0.0248	-1.1930	0.1166
GARCH(1; 2, 2)	0.9703	0.0119	81.2250	0.0000

Table 5.52.1a presents the results of the BEKK-MVGARCH model estimated for the bivariate relationship between the US insurance sector and the UK stock market. The ARCH and GARCH coefficients of the BEKK-MVGARCH model should be regarded as transmission coefficients. To better understand the transmission mechanism studied here, refer to equation 5.12a, 5.12b, 5.13a, 5.13b and 5.13c. The variable C(1) in Table 5.52.1a corresponds to the constant term in the mean equation (5.12a) of the first variable, in this case the US insurance sector. The A (i, j) variables corresponds to the (i, j) element of C, the upper triangular matrix in 5.12b; ARCH (1; i, j) is the (i, j) element of the ARCH coefficient matrix, A_1 while GARCH (1; i, j) is the (i, j) element of the GARCH coefficient matrix, B_1 in equation 5.12b. This structure enables us to examine the

multivariate normality when estimating MVGARCH models.

spillover effects between the markets[283]. We note that in the BEKK-MVGARCH model all the coefficients are estimated simultaneously by maximum likelihood and are valid for each variance and covariance equations when we write them out separately as in equation 5.13b and 5.13c.

All the univariate ARCH and the GARCH terms in the model for the US insurance sector and the UK stock market index (Table 5.52.1a) appear to be significant. Interpreting these results in terms of the volatility of the US insurance sector, for example; we should use equation 5.13b. With the exception of the GARCH (1; 1, 2) coefficient, all the univariate ARCH and GARCH coefficients in Table 5.52.1a are significant at the 1% level. This very high number of significant transmission coefficients is indicative of high volatility spillover effects between the US insurance sector and the UK stock market index. Judging by the level to the t statistics on the coefficients, It appears that the UK stock market transmit significant volatility to the US insurance sector although it also receives volatility from the US insurance sector.

The strength of the UK transmission is very interesting suggesting perhaps that US insurance sector might be heavily exposed to the UK stock market index. Or, perhaps the big players on the international insurance markets are based in the UK and they therefore assume the leading role across the international sector. Overall, the results suggest that there are substantial interactions between the two indices both in terms of variance transmission and covariance transmission. The

[283] The ARCH and GARCH parameters are based on the ordering of the variables given in the title of the Table. A USINS and UKM ordering for example would therefore mean that the GARCH (1; 1, 1) is the lagged GARCH volatility parameter for the US insurance sector while the

model estimated was also reasonably very well specified. Post estimation diagnostics indicate that there are no autocorrelation left in the standardised residuals from the estimated model. An example of the complete MVGARCH estimation results is given in Appendix 5.1c.

Next, we looked at the evidence for volatility spillovers between the US pharmaceuticals sector and the UK stock index (Table 5.52.1b). Of the eight ARCH and GARCH coefficients, five were significant at the 1% level and one at the 10% level. The remaining two, ARCH (1; 1, 2) and GARCH (1; 1, 2), which are both covariance terms were insignificant. Since the post estimation diagnostic were reasonable and model did converge, we believe that the model is well specified.

Table 5.52.1b: Volatility transmission between US Pharmaceuticals sector and the UK stock market using the BEKK-MVGARCH model. Variable ordered as USPHA and UKM respectively

Estimated Coefficients				
	Value	Std.Error	t value	Pr(>|t|)
C(1)	0.0038	0.0010	3.7979	0.0001
C(2)	0.0020	0.0008	2.5530	0.0054
A(1, 1)	0.0034	0.0010	3.4777	0.0003
A(2, 1)	0.0003	0.0049	0.0597	0.4762
A(2, 2)	0.0093	0.0020	4.7223	0.0000
ARCH(1; 1, 1)	0.1863	0.0324	5.7522	0.0000
ARCH(1; 2, 1)	-0.0468	0.0356	-1.3168	0.0942
ARCH(1; 1, 2)	0.0073	0.0645	0.1133	0.4549
ARCH(1; 2, 2)	0.3062	0.0462	6.6283	0.0000
GARCH(1; 1, 1)	0.9773	0.0128	76.2287	0.0000
GARCH(1; 2, 1)	0.0436	0.0195	2.2378	0.0128
GARCH(1; 1, 2)	-0.0073	0.0474	-0.1532	0.4392
GARCH(1; 2, 2)	0.8365	0.0609	13.7375	0.0000

GARCH (1; 2, 2) parameter will be to the GARCH volatility parameter for the UK stock market. This sequence of presentation is maintained throughout the chapter.

The evidence here (Table 5.52.1b) suggests that there is a significant volatility transmission from the US pharmaceuticals sector to the UK stock market. The t statistics for the GARCH parameter for the US pharmaceuticals sector [GARCH (1; 1, 1)] is higher than that for the UK stock market index [GARCH (1; 2, 2)]. Clearly, UK stock market volatility is highly affected by the US pharmaceutical sector due perhaps to the dominant role US pharmaceutical conglomerates.

The evidence for volatility spillover between the US IT hardware sector and the UK stock market index (Table 5.52.1c) suggests that there were significant volatility transmission from the US IT hardware sector into the UK stock market. Although the GARCH parameters for both indices were significant at the 1% level, the t statistics for the US IT hardware sector (47.8) was over four times higher than one for the UK stock index (9.8). The US IT hardware sector GARCH covariance parameter [GARCH (1; 1, 2)] was marginal while the UK stock index GARCH covariance parameter [GARCH (1; 2, 1)] was significant at the 10% level. This suggests that US IT hardware sector had the more complete transmission structure for it variance equation (a version of equation 5.13b and 5.13c) because it affected by both the UK stock index's GARCH volatility parameter and its GARCH covariance parameter. However volatility transmission from the US IT hardware sector into the UK stock market was more emphatic. This is due perhaps to the leading role played by US semiconductor firms and chip manufactures such as Intel across the international IT hardware sector.

Table 5.52.1c: Volatility transmission between US IT Hardware sector and the UK stock market using the BEKK-MVGARCH model. Variable ordered as USPHA and UKM respectively

Estimated Coefficients				
	Value	Std.Error	t value	Pr(>|t|)
C(2)	0.0020	0.0008	2.6168	0.0045
A(1, 1)	0.0028	0.0025	1.1108	0.1335
A(2, 1)	-0.0097	0.0104	-0.9289	0.1766
A(2, 2)	0.0036	0.0279	0.1288	0.4488
ARCH(1; 1, 1)	0.2298	0.0305	7.5369	0.0000
ARCH(1; 2, 1)	0.0417	0.0215	1.9417	0.0263
ARCH(1; 1, 2)	-0.1541	0.0923	-1.6692	0.0478
ARCH(1; 2, 2)	0.2929	0.0502	5.8372	0.0000
GARCH(1; 1, 1)	0.9546	0.0200	47.7726	0.0000
GARCH(1; 2, 1)	0.0296	0.0194	1.5249	0.0639
GARCH(1; 1, 2)	0.1066	0.0855	1.2463	0.1065
GARCH(1; 2, 2)	0.7968	0.0812	9.8120	0.0000

Finally, we looked at the volatility spillover evidence between the US retail sector and the UK stock market index (Table 5.52.1d). The GARCH volatility parameters for both indices were significant at the 1% level although a higher t statistics (38.6) was reported for the US retail sector GARCH volatility parameter. This suggests that volatility spillovers from the US retail sector are higher than vice versa. Once again, one of the GARCH covariance term [GARCH (1; 1, 2)] – The US retail sector GARCH covariance coefficient – was insignificant, which suggests that in this case, the UK stock index has the most complete volatility transmission model because its current volatility level is affected by both the lagged volatility emanating from the US retail sector, and the conditional covariance between the US retail sector and the UK stock index with the GARCH (1; 2, 1) coefficient being significant at the 10% level.

Table 5.52.1d: Volatility transmission between US retail sector and the UK stock market using the BEKK-MVGARCH model. Variable ordered as USRET and UKM respectively

Estimated Coefficients				
	Value	Std.Error	t value	Pr(>|t|)
C(2)	0.0017	0.0008	2.2264	0.0131
A(1, 1)	0.0048	0.0017	2.8639	0.0022
A(2, 1)	0.0028	0.0048	0.5736	0.2832
A(2, 2)	0.0102	0.0024	4.1751	0.0000
ARCH(1; 1, 1)	0.3007	0.0397	7.5735	0.0000
ARCH(1; 2, 1)	0.0255	0.0364	0.7025	0.2413
ARCH(1; 1, 2)	0.0270	0.0652	0.4143	0.3394
ARCH(1; 2, 2)	0.2813	0.0517	5.4412	0.0000
GARCH(1; 1, 1)	0.9557	0.0248	38.5827	0.0000
GARCH(1; 2, 1)	0.0411	0.0283	1.4514	0.0735
GARCH(1; 1, 2)	-0.0673	0.0679	-0.9903	0.1612
GARCH(1; 2, 2)	0.8015	0.0816	9.8160	0.0000

Overall the results indicate that a valid volatility transmission mechanism exists between the selected US sectoral stock market. The US pharmaceuticals sector appears to be the most important US sectoral market in terms of their effects on overall UK stock market volatility. Lagged volatility emanating for the US pharmaceuticals sector is found to have the largest impact on UK stock market volatility transmitting the most conditional second moment information. The results are interesting for both portfolio managers who make international asset allocation decisions and traders who are involved in volatility and correlation trading. The results would also be invaluable to those involved in the monitoring of international financial stability.

5.5.2.2 Volatility Transmission Results for spillovers from selected European sectors into the UK stock market.

We now turn our attention to the evidence for volatility transmission between the selected European sectors and the UK stock market index. As noted earlier, we estimated a BEKK-MVGARCH model for the bilateral relationships examined in this chapter. However, the nonlinear optimisation routines and computational requirements for the BEEK-MVGARCH model are such that sometimes the estimated model will fail to converge. Without convergence, the coefficient estimates could not be relied upon. Whenever this happens, we opted for the less general but equally positive definite vector diagonal vec model described in (5.18) above. This was the case for three of the BEKK-MVGARCH models estimated between the European sectoral stock markets and the UK stock market. They are the BEKK-MVGARCH model for transmission between the European insurance sector and the UK stock market, between the European pharmaceutical sector and the UK stock market and, between the European IT hardware sector and the UK stock market. A valid BEKK-MVGARCH model was estimated for the transmission mechanism between the European retail sector and the UK stock market.

The alternative vector diagonal-vec MVGARCH models estimated for the three cases above where surprisingly remarkably robust. They are given in Table 5.52.2a, Table 5.52.2b, Table 5.52.2b and Table 5.52.2c. These results could be interpreted in a similar as done for the ARCH and GARCH terms in the various BEKK-MVGARCH models examined to the relationship between the US sectors and the UK stock market.

The results in Table 5.52.2a indicate that while a two-way transmission mechanism exists between the European insurance sector and the UK stock market index, volatility transmitted from the European insurance sector into the UK market were higher; judged on the basis of the size to t statistics of the estimated GARCH coefficients – 50.66 for the European insurance sector and 20.77 for the UK stock index.

The vector diagonal-vec MVGARCH model for the transmission mechanism between the European pharmaceutical sectors and the UK stock market index is somewhat inconclusive in terms of which index transmits the most volatility across to the other (Table 5.52.2b). While both GARCH volatility coefficients are significant at the 1% level, the size of the t statistics on these coefficients is very close – 8.2 for the European insurance sector and 9.6 for the UK stock index. It is clear nonetheless, there exists significant volatility spillovers between the two.

Table 5.52.2a: Volatility transmission between the European insurance sector and the UK stock market using the Vector-diagonal MVGARCH model. Variable ordered as EUINS and UKM respectively

	Estimated Coefficients			
	Value	Std.Error	t value	Pr(>|t|)
C(1)	0.0027	0.0009	3.0280	0.0013
C(2)	0.0024	0.0008	3.2000	0.0007
A(1, 1)	0.0092	0.0008	11.6850	0.0000
A(2, 1)	0.0057	0.0011	5.3810	0.0000
A(2, 2)	0.0075	0.0009	8.0480	0.0000
ARCH(1; 1)	0.3888	0.0249	15.5920	0.0000
ARCH(1; 2)	0.3330	0.0319	10.4230	0.0000
GARCH(1; 1)	0.8626	0.0170	50.6590	0.0000
GARCH(1; 2)	0.8391	0.0404	20.7730	0.0000

Table 5.52.2b: Volatility transmission between European Pharmaceuticals sector and the UK stock market using the Vector-diagonal MVGARCH model. Variable ordered as EUPHA and UKM respectively

Estimated Coefficients				
	Value	Std.Error	t value	Pr(>|t|)
C(1)	0.0034	0.0008	4.0390	0.0000
C(2)	0.0020	0.0008	2.5450	0.0056
A(1, 1)	0.0110	0.0043	2.5510	0.0055
A(2, 1)	0.0066	0.0017	3.7630	0.0001
A(2, 2)	0.0098	0.0017	5.6880	0.0000
ARCH(1; 1)	0.2087	0.0463	4.5080	0.0000
ARCH(1; 2)	0.3325	0.0449	7.4010	0.0000
GARCH(1; 1)	0.8613	0.1047	8.2260	0.0000
GARCH(1; 2)	0.7740	0.0803	9.6430	0.0000

Table 5.52.2c: Volatility transmission between European IT Hardware sector and the UK stock market using the Vector-diagonal MVGARCH model. Variable ordered as EUIT and UKM respectively

Estimated Coefficients				
	Value	Std.Error	t value	Pr(>|t|)
C(1)	0.0048	0.0013	3.7230	0.0001
C(2)	0.0021	0.0008	2.7580	0.0030
A(1, 1)	0.0066	0.0009	7.1200	0.0000
A(2, 1)	0.0076	0.0018	4.1690	0.0000
A(2, 2)	0.0064	0.0011	6.1060	0.0000
ARCH(1; 1)	0.3125	0.0261	11.9870	0.0000
ARCH(1; 2)	0.3449	0.0321	10.7480	0.0000
GARCH(1; 1)	0.9376	0.0105	89.4460	0.0000
GARCH(1; 2)	0.8215	0.0356	23.1050	0.0000

Table 5.52.2c gives the results for the estimated volatility transmission model for the European IT hardware sector and the UK stock market index. The estimated GARCH coefficients for both indices are significant at the 1% level. However, there is marked difference between sizes of the estimated t statistics. The t statistics for the GARCH coefficient for the European IT hardware sector is 89.5 and for the UK stock index the estimated t statistics is 23.1.

The result for this model (Table 5.52.2c) is striking. While volatility can be transmitted between the European IT hardware sector and the UK stock market index, the size of the estimated t statistics suggests that four times more volatility is transmitted from the European IT hardware sector in the UK stock market. On the basis of the t statistics, the European IT Hardware sector is the sector with the highest impact on the UK stock market and transmits the largest volatility. UK stock market volatility is therefore highly sensitive to volatility in the European IT hardware sector.

Table 5.52.2d: Volatility transmission between European retail sector and the UK stock market using the BEKK-MVGARCH model. Variable ordered as EURET and UKM respectively

	Estimated Coefficients			
	Value	Std.Error	t value	Pr(>|t|)
C(1)	0.0028	0.0008	3.3570	0.0004
C(2)	0.0025	0.0008	3.2124	0.0007
A(1, 1)	0.0029	0.0075	0.3880	0.3491
A(2, 1)	0.0102	0.0214	0.4747	0.3176
A(2, 2)	0.0041	0.0497	0.0834	0.4668
ARCH(1; 1, 1)	0.2107	0.0567	3.7181	0.0001
ARCH(1; 2, 1)	0.3168	0.0385	8.2242	0.0000
ARCH(1; 1, 2)	0.2106	0.0645	3.2657	0.0006
ARCH(1; 2, 2)	-0.1256	0.0542	-2.3175	0.0104
GARCH(1; 1, 1)	0.7830	0.0351	22.3309	0.0000
GARCH(1; 2, 1)	-0.1626	0.0451	-3.6032	0.0002
GARCH(1; 1, 2)	0.2766	0.0780	3.5478	0.0002
GARCH(1; 2, 2)	0.8951	0.0699	12.8125	0.0000

A valid BEKK-MVGARCH model was estimated for the transmission of volatility between the European retail sector and the UK stock market. All estimated ARCH and GARCH coefficients were significant at either the 1% or 5% levels. The evidence suggests a two-way volatility transmission mechanism exists between the two indices although it seems that more volatility is spills over from the European retail sector into the UK stock market than vice versa. The estimated t statistics is 22.3 for the European retail sector and 12.8 for the UK stock market.

Overall, the results for the European sectoral market and UK stock market volatility indicate that there is significant information flow between the selected European sectors and the UK stock market. We find that the European IT hardware sector is the sectoral stock market with the greatest impact on UK stock market volatility. This evidence is very important especially for portfolio managers with large exposures across the European IT hardware sector and some exposure in the UK stock market. Asset allocation decisions will be better informed with this evidence.

5.5.2.3 Volatility Transmission Results for spillovers from the US and European stock market into the UK stock market.

In this section we study a series of three-variable MVGACH models to examine the cross-market and cross-sectoral volatility spillovers for all the three markets studied. In this analysis only vector-diagonal MVGARCH models were found to valid. Although some BEKK-MVGARCH models looked reasonable, none of their post estimation diagnostics were robust enough to guarantee the validity of the model. No convergence was reached despite trying high iteration levels, different step sizes and different nonlinear optimisation algorithms.

The first three-variable MVGARCH model estimated is a volatility transmission model between the US, European and UK stock indices (Table 5.52.3). Although the vector-diagonal MVGARCH model is less complicated than the BEKK-

MVGARCH model, there were still twelve parameters plus three mean equation parameters to be estimated.

Table 5.52.3: Volatility transmission between US, European and the UK stock market using a three-variable Vector-diagonal MVGARCH model. Variable ordered as USM, EUM and UKM respectively

Estimated Coefficients	Value	Std.Error	t value	Pr(>|t|)
C(1)	0.0030	0.0007	4.4770	0.0000
C(2)	0.0025	0.0007	3.6530	0.0001
C(3)	0.0024	0.0007	3.2690	0.0006
A(1, 1)	0.0017	0.0004	4.6900	0.0000
A(2, 1)	0.0018	0.0007	2.8270	0.0024
A(3, 1)	0.0014	0.0005	2.7470	0.0031
A(2, 2)	0.0028	0.0004	6.3580	0.0000
A(3, 2)	0.0015	0.0003	4.6700	0.0000
A(3, 3)	0.0020	0.0004	5.3650	0.0000
ARCH(1; 1)	0.1895	0.0160	11.8070	0.0000
ARCH(1; 2)	0.2315	0.0172	13.4300	0.0000
ARCH(1; 3)	0.1839	0.0189	9.7470	0.0000
GARCH(1; 1)	0.9787	0.0037	267.4270	0.0000
GARCH(1; 2)	0.9604	0.0071	134.6270	0.0000
GARCH(1; 3)	0.9743	0.0053	183.0750	0.0000

All of the estimated ARCH and GARCH coefficient were significant at the 1% level. There is evidence of a high level of transmission between these markets. Interestingly, the US stock market appears to be the market the produces the highest volatility transmission effects among the three markets. The estimated t statistics of the univariate GARCH parameter for the US stock index is 267.43 compared to 134.63 for the European stock index and 183.1 for the UK stock index. Our evidence confirms exiting anecdotal evidence among practitioners which suggests that large movement in the US stock markets always affects other major markets especially European stock markets and the Japanese stock market. Our evidence suggests that UK stock market volatility is most influenced by lagged US stock market volatility.

5.5.2.4 Volatility Transmission Results for inter-sectoral spillovers from the US and European sectoral stock market into the UK sectoral stock market.

In this section we analyse four three-variable inter-sectoral volatility spillover models in each of the four sectors across all three markets. The result for the inter-sectoral model for the insurance sectors in the three markets is provided in the Table 5.52.4a. Table 5.52.4b give the result for the pharmaceuticals sector, Table 5.52.4c the result for the IT hardware sector and Table 5.52.4d those for the retail sector.

Table 5.52.4a: Volatility transmission between US Insurance sector, European insurance sector and the UK insurance sector using a three-variable Vector-diagonal MVGARCH model. Variable ordered as USINS, EUINS and UKINS respectively

	Estimated Coefficients			
	Value	Std.Error	t value	Pr(>|t|)
C(1)	0.0033	0.0008	4.1990	0.0000
C(2)	0.0028	0.0009	2.9390	0.0017
C(3)	0.0018	0.0014	1.3110	0.0951
A(1, 1)	0.0054	0.0007	7.7920	0.0000
A(2, 1)	0.0020	0.0006	3.4290	0.0003
A(3, 1)	0.0049	0.0015	3.3340	0.0004
A(2, 2)	0.0062	0.0008	7.3820	0.0000
A(3, 2)	0.0059	0.0014	4.0830	0.0000
A(3, 3)	0.0122	0.0016	7.4660	0.0000
ARCH(1; 1)	0.3162	0.0232	13.6440	0.0000
ARCH(1; 2)	0.2874	0.0228	12.6090	0.0000
ARCH(1; 3)	0.2303	0.0314	7.3330	0.0000
GARCH(1; 1)	0.9242	0.0111	83.2700	0.0000
GARCH(1; 2)	0.9292	0.0131	70.9200	0.0000
GARCH(1; 3)	0.8983	0.0300	29.9360	0.0000

The evidence for the insurance sector inter-sectoral volatility transmission across the three markets suggests that sectoral volatility is transmitted across the sectors in the three markets but the US insurance sector volatility transmission into the

UK insurance sector is higher than the impact of volatility transmitted from the European insurance sector into the UK insurance sector. This means that when studied together the US insurance sector is the more important sector and transmits the largest volatility into the insurance sector in the other markets.

Table 5.52.4b: Volatility transmission between US pharmaceuticals sector, European pharmaceuticals sector and the UK pharmaceuticals sector using a three-variable Vector-diagonal MVGARCH model. Variable ordered as USPHA, EUPHA and UKPHA respectively

	Estimated Coefficients			
	Value	Std.Error	t value	Pr(>|t|)
C(1)	0.0040	0.0010	3.8950	0.0001
C(2)	0.0035	0.0008	4.1590	0.0000
C(3)	0.0037	0.0012	3.0660	0.0011
A(1, 1)	0.0050	0.0013	3.8110	0.0001
A(2, 1)	0.0033	0.0016	2.1300	0.0167
A(3, 1)	0.0022	0.0006	3.4330	0.0003
A(2, 2)	0.0064	0.0017	3.8330	0.0001
A(3, 2)	0.0022	0.0007	3.0570	0.0012
A(3, 3)	0.0034	0.0016	2.0730	0.0193
ARCH(1; 1)	0.1795	0.0286	6.2780	0.0000
ARCH(1; 2)	0.1677	0.0443	3.7870	0.0001
ARCH(1; 3)	0.1461	0.0272	5.3690	0.0000
GARCH(1; 1)	0.9680	0.0118	82.1280	0.0000
GARCH(1; 2)	0.9370	0.0349	26.8250	0.0000
GARCH(1; 3)	0.9804	0.0086	114.6520	0.0000

Looking at Table 5.52b we see that all the univariate ARCH and GARCH coefficients are significant were significant at the 1% level suggesting evidence of significant volatility transmission between the pharmaceutical sectors across three markets. The largest t statistics for a GARCH volatility coefficient was the UK pharmaceuticals GAECH coefficient, 114.6 compared to 26.8 for the European pharmaceuticals sector and 82.1 for the US pharmaceuticals sector.

Table 5.52.4c reports results for volatility transmission between the IT hardware sections in the three markets. ALL the estimated univariate ARCH and GARCH coefficients were significant at the 1% level. The size of t statistics reveals an almost even level of transmission between the UK IT hardware sector and the US IT hardware sector. The European IT hardware sector seem had the smallest t statistics and therefore receives the most volatility transmission from the US and UK IT hardware sector.

Table 5.52.4c: Volatility transmission between US IT hardware sector, European IT hardware sector and the UK IT hardware sector using a three-variable Vector-diagonal MVGARCH model. Variable ordered as USINS, EUINS and UKINS respectively

Estimated Coefficients				
	Value	Std.Error	t value	Pr(>|t|)
C(1)	0.0037	0.0013	2.9340	0.0017
C(2)	0.0049	0.0013	3.7800	0.0001
C(3)	0.0064	0.0030	2.1220	0.0171
A(1, 1)	0.0044	0.0008	5.3860	0.0000
A(2, 1)	0.0020	0.0008	2.5590	0.0053
A(3, 1)	0.0032	0.0021	1.5300	0.0633
A(2, 2)	0.0055	0.0008	7.3010	0.0000
A(3, 2)	0.0035	0.0020	1.7500	0.0402
A(3, 3)	0.0190	0.0011	18.0660	0.0000
ARCH(1; 1)	0.2123	0.0205	10.3680	0.0000
ARCH(1; 2)	0.2570	0.0195	13.1740	0.0000
ARCH(1; 3)	0.2895	0.0149	19.4680	0.0000
GARCH(1; 1)	0.9703	0.0057	170.6250	0.0000
GARCH(1; 2)	0.9553	0.0072	132.1030	0.0000
GARCH(1; 3)	0.9319	0.0056	167.4040	0.0000

Table 5.52.4d: Volatility transmission between US retail sector, European retail sector and the UK retail sector using a three-variable Vector-diagonal MVGARCH model. Variable ordered as USRET, EURET and UKRET respectively

Estimated Coefficients				
	Value	**Std.Error**	**t value**	**Pr(>|t|)**
C(1)	0.0031	0.0010	3.1140	0.0010
C(2)	0.0022	0.0009	2.5860	0.0049
C(3)	0.0021	0.0010	2.0410	0.0208
A(1, 1)	0.0048	0.0009	5.5430	0.0000
A(2, 1)	0.0007	0.0003	2.3580	0.0093
A(3, 1)	0.0008	0.0004	2.1130	0.0175
A(2, 2)	0.0023	0.0006	3.9330	0.0000
A(3, 2)	0.0009	0.0004	2.0780	0.0190
A(3, 3)	0.0026	0.0009	2.7730	0.0028
ARCH(1; 1)	0.2431	0.0243	9.9980	0.0000
ARCH(1; 2)	0.1459	0.0163	8.9710	0.0000
ARCH(1; 3)	0.1331	0.0233	5.7090	0.0000
GARCH(1; 1)	0.9573	0.0086	110.9060	0.0000
GARCH(1; 2)	0.9848	0.0039	250.4200	0.0000
GARCH(1; 3)	0.9863	0.0055	178.4300	0.0000

Table 5.52.4d gives the results for the inter-sectoral volatility in the retail sector. All of the ARCH and GARCH coefficients were significant at the 1% level indicating that volatility is indeed transmitted across the retail sectors in the three markets. The estimated t statistics for the GARCH coefficients suggests that the highest transmission effect is found in the European retail sector volatility, which has a t statistics of 250.4 compared to 110.9 for the US retail sector and 178.4 for the UK sector.

In summary, our analysis of the three-variable vector-diagonal MVGARCH model produced some interesting results about the dynamics of volatility across the four sectors in the three markets studied. There is evidence of significant inter-sectoral volatility in each of the four sectors. The highest spillover effect in terms of the t statistics of significant univariate GARCH coefficients was for the volatility transmitted from the European retails sector into the US and UK retail sectors.

For a rejoinder on all our analysis so far, an overall summary of the volatility transmission results is provided in Table 5.52.4e below.

Table 5.52.4e: Summary of Volatility transmission Results

Volatility Transmission Scenario	Summary of Results
Volatility Transmission model for between US sectoral stock markets and the UK stock market	High volatility spillovers between US sectoral markets and the UK stock market; US Pharmaceuticals appears to be most important for UK stock market
Volatility Transmission model for between European sectoral stock markets and the UK stock market	High volatility spillovers between European sectoral markets and the UK stock market; the European IT Hardware sector appears to be most important for UK stock market
Three-variable volatility transmission model for the US, European and UK stock markets	Strong evidence of volatility spillovers between the three markets with the US stock market having the greatest impact on the other markets
Three-variable inter-sectoral volatility transmission model for the US, European and UK sectoral stock markets	High levels of inter-sectoral volatility spillover exists; significant volatility is transmitted from the European retails sector into the US and UK retail sectors

5.5.2.5 Volatility Transmission Results for spillovers from the US and European stock market into the UK stock market – An alternative distributional parameterisation

In this section a three variable BEKK-MVARCH model with multivariate conditional student t density instead of a multivariate conditional normal density is estimated. This analysis is carried out in order to address the question non-normal returns in equity market which has been raised in the literature. A number of the models estimated in previous sections were carried using the student t density. The results did not change but a slightly improved fit was obtained. We have therefore decided to report these result. We however report the result for a valid three-variable BEKK-MVGARCH model (Table 5.52.5) with multivariate student t density for the volatility transmission between the broad market indices – the US stock market index, the European stock market index and the UK stock market index – to illustrate the point. Obviously, the model contains large number of coefficients. There are twenty four conditional covariance matrix coefficients plus three mean equation coefficients. The estimated degrees of freedom is equal to 6, which is reasonable for financial data. The results obtained were slightly mixed five out nine of the univariate GARCH parameters were significant at the 1% or 5% level while six out of nine of the ARCH parameters were significant at the 1%, 5% or 10% levels. This is a reasonably good results; suggesting that there is a high level of interaction between market volatilities across the three stock markets. These results are consistent with those obtained for the three-variable vector diagonal estimated for the three markets in Table 5.52.3. The lagged US stock market volatility [the GARCH (1; 1, 1) parameter in Table 5.52.3] appears to be the most significant on the basis of the estimated t statistics followed by the UK [GARCH (1; 3, 3) parameter] and Europe [GARCH (1; 2, 2) parameter][284]. The US market therefore contains the most information required to accentuate volatility in Europe or the UK.

[284] These are based on the ordering of the variables for estimation. See Table title.

Table 5.52.5: Volatility transmission between US, European and the UK stock market using a three-variable BEKK-MVGARCH model with multivariate conditional student t density. Variable ordered as USM, EUM and UKM respectively – *estimated degrees of freedom = 6*

Estimated Coefficients

	Value	Std.Error	t value	Pr(>|t|)
C(1)	0.0027	0.0008	3.3728	0.0004
C(2)	0.0022	0.0010	2.1565	0.0157
C(3)	0.0020	0.0010	1.9687	0.0247
A(1, 1)	0.0015	0.0027	0.5346	0.2965
A(2, 1)	-0.0059	0.0181	-0.3276	0.3717
A(3, 1)	-0.0065	0.0189	-0.3456	0.3649
A(2, 2)	0.0038	0.0312	0.1203	0.4521
A(3, 2)	-0.0041	0.0986	-0.0416	0.4834
A(3, 3)	0.0001	5.3437	0.0000	0.5000
ARCH(1; 1, 1)	0.2762	0.0630	4.3815	0.0000
ARCH(1; 2, 1)	0.1046	0.0738	1.4176	0.0784
ARCH(1; 3, 1)	-0.0750	0.0716	-1.0482	0.1474
ARCH(1; 1, 2)	0.0562	0.0782	0.7185	0.2363
ARCH(1; 2, 2)	0.3757	0.0940	3.9991	0.0000
ARCH(1; 3, 2)	0.1560	0.0873	1.7865	0.0372
ARCH(1; 1, 3)	-0.0824	0.0732	-1.1260	0.1303
ARCH(1; 2, 3)	-0.1610	0.1080	-1.4902	0.0683
ARCH(1; 3, 3)	0.2196	0.0966	2.2735	0.0116
GARCH(1; 1, 1)	0.9454	0.0381	24.8143	0.0000
GARCH(1; 2, 1)	0.0229	0.0501	0.4573	0.3238
GARCH(1; 3, 1)	0.0887	0.0505	1.7561	0.0397
GARCH(1; 1, 2)	-0.0352	0.0694	-0.5070	0.3061
GARCH(1; 2, 2)	0.7523	0.1103	6.8217	0.0000
GARCH(1; 3, 2)	-0.0947	0.0959	-0.9870	0.1620
GARCH(1; 1, 3)	0.0698	0.0601	1.1606	0.1231
GARCH(1; 2, 3)	0.1824	0.1042	1.7515	0.0401
GARCH(1; 3, 3)	0.9365	0.0860	10.8905	0.0000

5.6 Summary and Conclusions

The empirical objective of this chapter was to examine the structure of time-varying bilateral correlation between the US and European sectoral stock markets and the UK stock market and, to investigate the extent to which sectoral market volatility in the US and European equity markets affects UK stock market volatility. We wish to assess the levels of volatility spillovers, emanating from the US and European markets, in the UK stock market. Understanding, at a sectoral level, the international and regional effects of UK stock market volatility and correlations is important question for a number of reasons.

Firstly, the levels of financial markets volatility and the correlations between the classes of related asses determines the expected returns on specific assets on asset portfolio. Understanding the dynamics or variations in correlations and volatility over time will lead to fair pricing of financial assets and better diversification and asset allocation decisions. This is particularly important for risk managers or portfolio managers who compute risk measures such as Value at Risk (VaR) or Expected shortfall (tail loss) on their portfolios because, they rely on the estimates of correlations between returns on financial instruments in their portfolios and on the volatility of those returns for key decisions.

Second, the extant literature suggest that during market downturns financial market volatility increases and associated correlation between markets also increases leading a synchronised pattern of highly volatile and correlated financial markets. This is the bear market phenomenon. An assessment of this evidence for the relationship between US sectoral markets, European sectoral markets and, the UK broad market and sectoral stock markets will provide very useful information which could potentially answer a number of interesting questions. For example, we could extract information about the levels of sectoral and market-wide volatility or correlations which could be vital in addressing certain concerns about UK financial stability. Recent financial market turbulence such as the Collapse of the Russian bond market and Asian financial crises illustrates the importance of accurately determining the correlation structure of international asset returns in order to determine critical turning points in international financial markets. Conditional correlation estimates can also be used as rough guide of the extent of financial integration between the markets studied.

Third, studying the extent of volatility spillovers from international sectoral stock markets into the UK stock market address both a UK financial stability question and a UK financial market integration question. Knowledge of the impact of international sectoral market volatility on UK financial market volatility could be used to develop early warning systems by those monitoring UK and international financial stability. The extent of volatility spillover between these markets can also be viewed (loosely) as indicative of the levels of capital market integration between markets. To the extent that market volatility and correlation are driven by exposures to common macroeconomic or other unobservable shocks significant volatility spillovers between markets may be construed as measures of levels of integration between the markets.

We follow Engle and Sheppard (2001) and Engle (2002a) and estimate DCC time-varying correlations between selected US sectoral markets and the UK markets and, between selected European sectoral market and the UK stock market. Conditional volatility spillovers between the markets are examined in the context of an MVGARCH model. Specifically, we utilise the symmetric positive definite BEKK-MVGARCH model suggested Engle and Kroner (1995). This model is perhaps the most general MVGARCH model and have been applied in a similar context by Kearney and Patton (2000) and Patton (2003).

This chapter has established the following key results:

- A valid time-varying correlation exits between the selected US and European sectoral markets and, the UK stock market. There is therefore a persistent variation in the correlation structure between these markets
- Average correlations between the selected US sectoral stock markets, the selected European sectoral stock markets and, the UK stock markets have increased over time.
- The Average correlation between the European sectoral markets and the UK stock market is higher than the average correlation between the US sectoral stock market and the UK stock market especially since the mid 1990. A sign of increased capital markets integration between European stock markets and the UK stock market from sectoral point of view.
- There are significant volatility spillovers between the US sectoral stock market and the UK stock market
    - The US pharmaceuticals sector is the most important US sectoral market in terms of their effects on overall UK stock market volatility.

Lagged volatility emanating for the US pharmaceuticals sector is found to have the largest impact on UK stock market volatility.

- There are significant volatility spillovers between European sectoral stock markets and the UK stock market.
    - The European IT hardware sector is the sectoral stock market with the greatest impact on UK stock market volatility
- There also exists significant trivariate volatility spillovers between the US, European and the UK stock markets due to number of valid three-variable MVGARCH models estimated.
    - In most of these scenarios, the US sectoral stock market volatility is found to have largest impact on UK stock market volatility.

APPENDIX 5.1a Additional Time-varying correlation results

Time-varying correlations between the UK and US sectoral stock markets

Table A5.1a: Estimation Results for DCC Estimation between UK stock market and US sectoral stock markets – six variable DCC model

```
MAXIMIZE - Estimation by BFGS
Convergence in     3 Iterations. Final criterion was  0.0000088 <  0.0000100
Weekly Data From 1988:12:16 To 2003:07:11
Usable Observations    761
Function Value                  -6686.30381098

   Variable                          Coeff        Std Error      T-Stat     Signif
*******************************************************************************
1.   PHI0(1)                      0.207053517  0.076156253       2.71880  0.00655195
2.   PHI0(2)                      0.366358212  0.081705777       4.48387  0.00000733
3.   PHI0(3)                      0.439995221  0.098616249       4.46169  0.00000813
4.   PHI0(4)                      0.317208521  0.110701850       2.86543  0.00416442
5.   PHI0(5)                      0.322362949  0.099710505       3.23299  0.00122502
6.   PHI0(6)                      0.309991537  0.063259451       4.90032  0.00000096
7.   PHI1(1)                     -0.024441061  0.042351436      -0.57710  0.56387116
8.   PHI1(2)                     -0.047850747  0.041381685      -1.15633  0.24754755
9.   PHI1(3)                     -0.108177295  0.036312656      -2.97905  0.00289142
10.  PHI1(4)                     -0.042902917  0.037813215      -1.13460  0.25654248
11.  PHI1(5)                     -0.052420752  0.035559102      -1.47419  0.14043135
12.  PHI1(6)                     -0.111132541  0.034283621      -3.24156  0.00118876
13.  OMEGA(1)                     1.399717062  0.076657414      18.25938  0.00000000
14.  OMEGA(2)                     0.323806339  0.038018788       8.51701  0.00000000
15.  OMEGA(3)                     0.121687352  0.010573120      11.50912  0.00000000
16.  OMEGA(4)                     0.132409718  0.023648576       5.59906  0.00000002
17.  OMEGA(5)                     0.141337613  0.025721090       5.49501  0.00000004
18.  OMEGA(6)                     0.013058649  0.004528894       2.88341  0.00393398
19.  ALPHA(1)                     0.112369872  0.015353978       7.31862  0.00000000
20.  ALPHA(2)                     0.167876198  0.008853829      18.96086  0.00000000
21.  ALPHA(3)                     0.035145619  0.001219498      28.81975  0.00000000
22.  ALPHA(4)                     0.044513276  0.002072131      21.48189  0.00000000
23.  ALPHA(5)                     0.063366574  0.003376289      18.76811  0.00000000
24.  ALPHA(6)                     0.043637527  0.001699593      25.67529  0.00000000
25.  BETA(1)                      0.596170614  0.016281518      36.61640  0.00000000
26.  BETA(2)                      0.790376280  0.007442731     106.19439  0.00000000
27.  BETA(3)                      0.951303784  0.001098419     866.06651  0.00000000
28.  BETA(4)                      0.949926323  0.001994483     476.27697  0.00000000
29.  BETA(5)                      0.924025716  0.002931817     315.17169  0.00000000
30.  BETA(6)                      0.955943222  0.001482683     644.73872  0.00000000

Correlations of Series Z(1)
Weekly Data From 1988:11:11 To 2003:07:11
Autocorrelations
     1:  0.0101447  0.0384078 -0.0103727 -0.0231212  0.0095520 -0.0190903 -
0.0496203 -0.0291913
     9: -0.0318587 -0.0077605 -0.0471709 -0.0336633


Ljung-Box Q-Statistics
Q(4-0) =            1.7107.  Significance Level 0.78877237
Q(8-0) =            4.6331.  Significance Level 0.79597737
Q(12-0)=            8.0866.  Significance Level 0.77832416
```

```
Correlations of Series Z(2)
Weekly Data From 1988:11:11 To 2003:07:11
Autocorrelations
     1:  0.0351870  0.0706609  0.0488884  0.0034727 -0.0559797  0.0558413
0.0471341  0.0113365
     9:  0.0914219  0.0145793  0.0197399 -0.0290793


Ljung-Box Q-Statistics
Q(4-0) =         6.6489.  Significance Level 0.15564902
Q(8-0) =        13.3068.  Significance Level 0.10172118
Q(12-0)=        20.9308.  Significance Level 0.05140315

Correlations of Series Z(3)
Weekly Data From 1988:11:11 To 2003:07:11
Autocorrelations
     1:  0.0156348  0.0500558 -0.0414305  0.0267083 -0.0322078  0.0211246 -
0.0160411  0.0011019
     9: -0.0208762  0.0336283 -0.0162367 -0.0667287


Ljung-Box Q-Statistics
Q(4-0) =         3.9915.  Significance Level 0.40716249
Q(8-0) =         5.3392.  Significance Level 0.72078410
Q(12-0)=        10.2374.  Significance Level 0.59514341

Correlations of Series Z(4)
Weekly Data From 1988:11:11 To 2003:07:11
Autocorrelations
     1: -0.0033381  0.0436110  0.0599710 -0.0516690 -0.0095908  0.0117322 -
0.0537469  0.0114186
     9:  0.0100622 -0.0011942  0.0646226  0.0055402


Ljung-Box Q-Statistics
Q(4-0) =         6.3071.  Significance Level 0.17735524
Q(8-0) =         8.8250.  Significance Level 0.35727439
Q(12-0)=        12.1827.  Significance Level 0.43112167

Correlations of Series Z(5)
Weekly Data From 1988:11:11 To 2003:07:11
Autocorrelations
     1:  0.0100374  0.0164595 -0.0050498  0.0082238 -0.0071102  0.0345086 -
0.0461614 -0.0564683
     9: -0.0067555  0.0502382  0.0100709 -0.0499891


Ljung-Box Q-Statistics
Q(4-0) =         0.3580.  Significance Level 0.98577196
Q(8-0) =         5.4452.  Significance Level 0.70910632
Q(12-0)=         9.4734.  Significance Level 0.66205606

Correlations of Series Z(6)
Weekly Data From 1988:11:11 To 2003:07:11
Autocorrelations
     1:  0.0126497  0.0678106  0.0012490 -0.0541555 -0.0366324  0.0645567 -
0.0432506 -0.0320210
     9:  0.0114480  0.0071344  0.0758863 -0.0256306

Ljung-Box Q-Statistics
Q(4-0) =         5.9292.  Significance Level 0.20449771
Q(8-0) =        12.4382.  Significance Level 0.13269725
Q(12-0)=        17.5793.  Significance Level 0.12907261
```

```
Correlations of Series ZSQ(1)
Weekly Data From 1988:11:11 To 2003:07:11
Autocorrelations
     1: -0.0335131  0.1006848 -0.0332498 -0.0071517 -0.0193141 -0.0214545
0.0456289 -0.0192152
     9: -0.0437646 -0.0195912  0.0311425 -0.0321680


Ljung-Box Q-Statistics
Q(4-0) =          9.5615.  Significance Level 0.04849874
Q(8-0) =         12.1064.  Significance Level 0.14651725
Q(12-0)=         15.4566.  Significance Level 0.21740831

Correlations of Series ZSQ(2)
Weekly Data From 1988:11:11 To 2003:07:11
Autocorrelations
     1:  0.0449750  0.0438735 -0.0018966 -0.0418927  0.0267812 -0.0578882
0.0029519 -0.0233016
     9:  0.0157341 -0.0195938 -0.0576643  0.0281761


Ljung-Box Q-Statistics
Q(4-0) =          4.3954.  Significance Level 0.35513488
Q(8-0) =          7.9719.  Significance Level 0.43622008
Q(12-0)=         11.6734.  Significance Level 0.47225362

Correlations of Series ZSQ(3)
Weekly Data From 1988:11:11 To 2003:07:11
Autocorrelations
     1:  0.0241632  0.0066131  0.0337934 -0.0045187 -0.0699411  0.0135101 -
0.0483629  0.0156743
     9: -0.0166455  0.0171728  0.0460391 -0.0207292


Ljung-Box Q-Statistics
Q(4-0) =          1.3789.  Significance Level 0.84784915
Q(8-0) =          7.3053.  Significance Level 0.50407529
Q(12-0)=          9.7370.  Significance Level 0.63902299

Correlations of Series ZSQ(4)
Weekly Data From 1988:11:11 To 2003:07:11
Autocorrelations
     1: -0.0081291  0.0116281  0.0496398 -0.0271652 -0.0482587 -0.0308079
0.0375416 -0.0204395
     9: -0.0239072  0.0633626  0.0149847 -0.0294697


Ljung-Box Q-Statistics
Q(4-0) =          2.6245.  Significance Level 0.62248431
Q(8-0) =          6.5762.  Significance Level 0.58297159
Q(12-0)=         10.9971.  Significance Level 0.52917014


Correlations of Series ZSQ(5)
Weekly Data From 1988:11:11 To 2003:07:11
Autocorrelations
     1:  0.0880292  0.0234709  0.0059764  0.0149311 -0.0408930  0.0343302 -
0.0272816 -0.0028231
     9: -0.0446124 -0.0183419  0.0145489  0.0638540


Ljung-Box Q-Statistics
Q(4-0) =          6.5830.  Significance Level 0.15963762
Q(8-0) =          9.3710.  Significance Level 0.31196947
Q(12-0)=         14.5257.  Significance Level 0.26840536
```

```
Correlations of Series ZSQ(6)
Weekly Data From 1988:11:11 To 2003:07:11
Autocorrelations
     1:  0.0599456  0.0039787  0.0325492 -0.0182963 -0.0202840  0.0333960 -
0.0065637 -0.0379647
     9: -0.0329001 -0.0378588  0.0058708  0.0035617


Ljung-Box Q-Statistics
Q(4-0) =          3.8509.  Significance Level 0.42656234
Q(8-0) =          6.1843.  Significance Level 0.62660075
Q(12-0)=          8.1775.  Significance Level 0.77110887


MAXIMIZE - Estimation by BFGS
Convergence in     1 Iterations. Final criterion was  0.0000022 <  0.0000100
Weekly Data From 1989:01:06 To 2003:07:11
Usable Observations    758
Function Value                   -903.40852232

   Variable                       Coeff        Std Error       T-Stat      Signif
*******************************************************************************
1.  ALPHA_C                    0.0213653381 0.0010553650     20.24450  0.00000000
2.  BETA_C                     0.9633454162 0.0021431982    449.48965  0.00000000
```

Figure A5.11 DCC time-varying correlations between the UK market and US sectoral stock markets

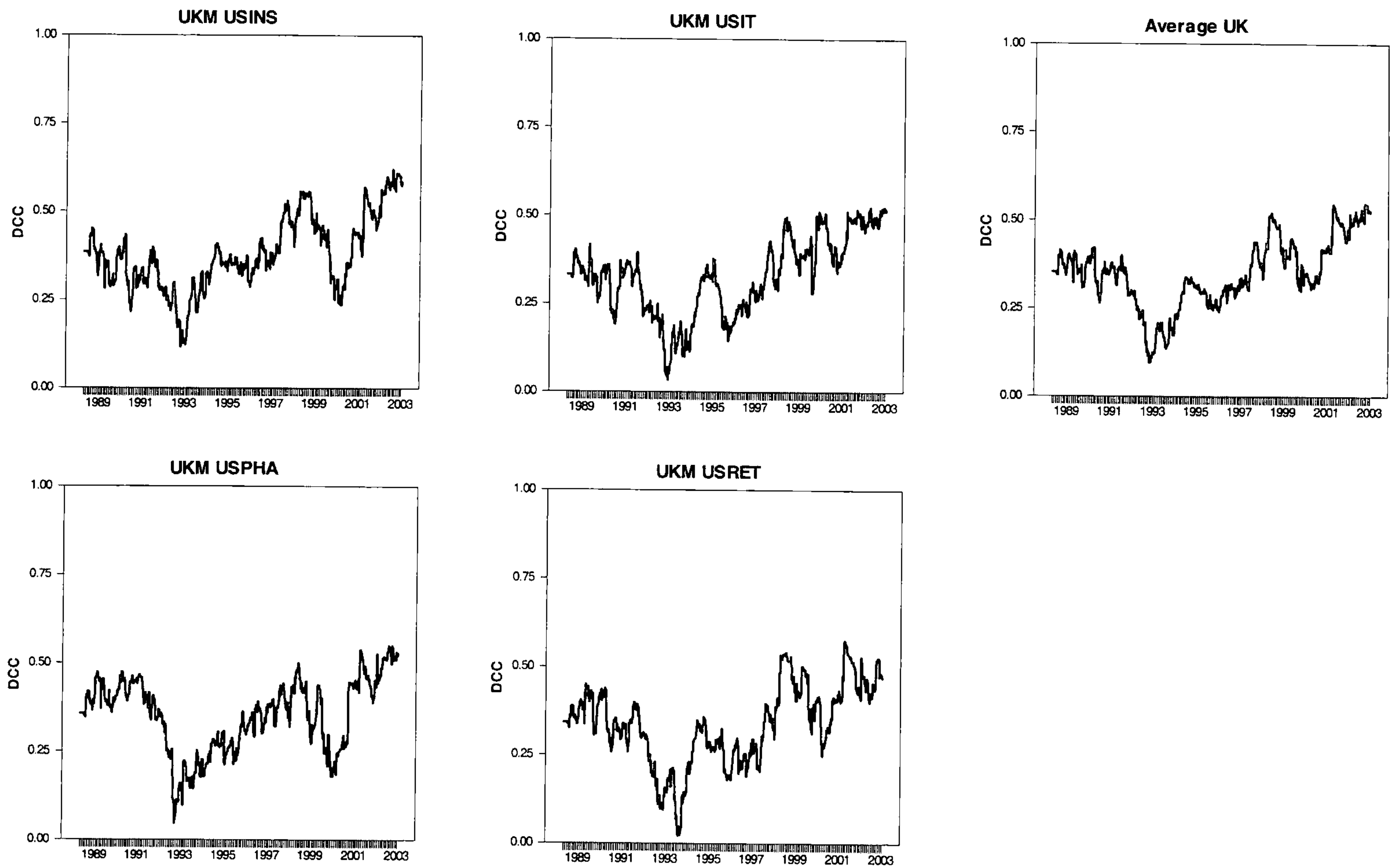


Figure A5.12 DCC time-varying correlations between the UK sectoral stock markets and US sectoral stock markets

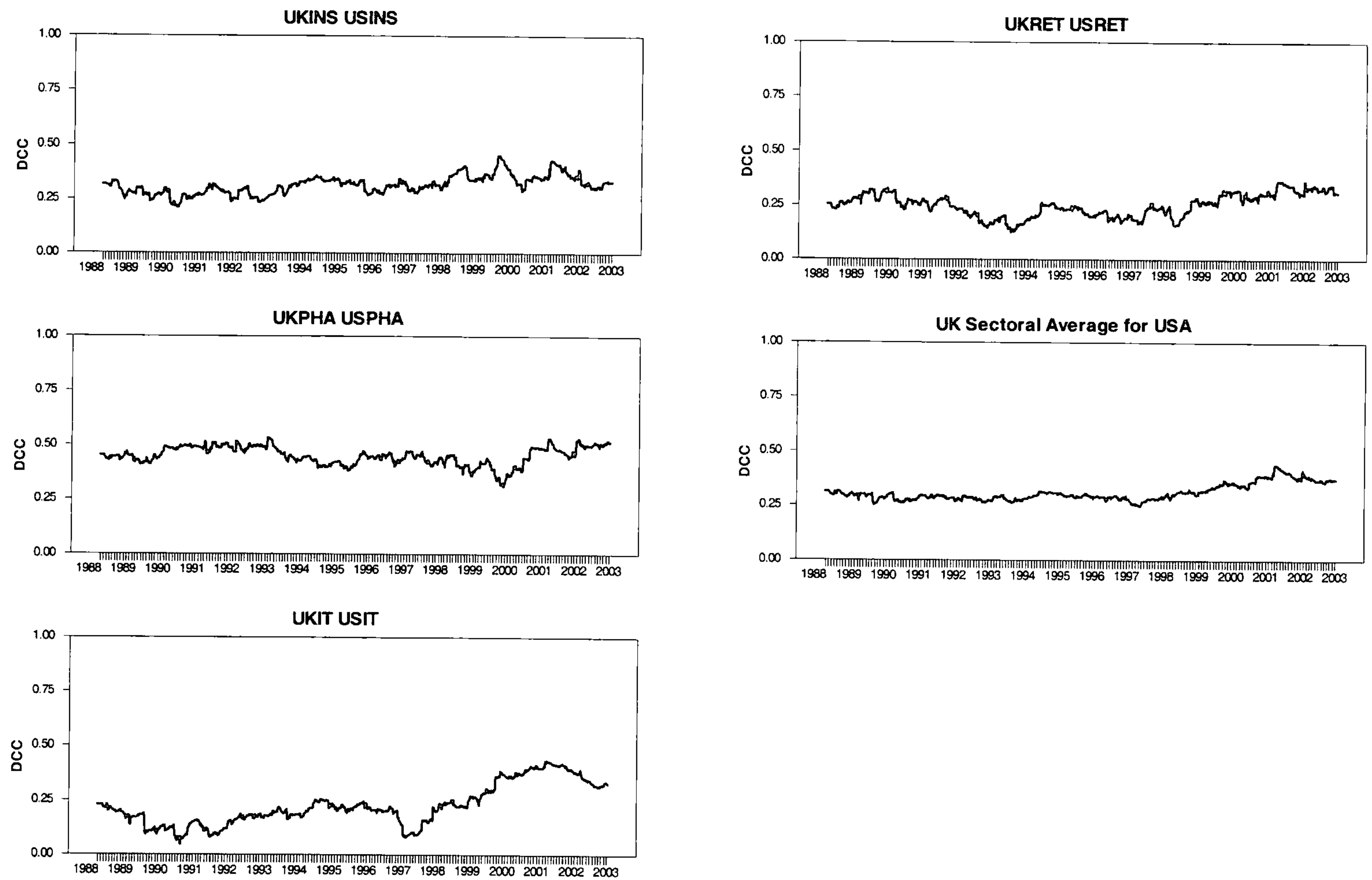


Figure A5.13 DCC time-varying correlations between the UK stock market and European sectoral stock markets

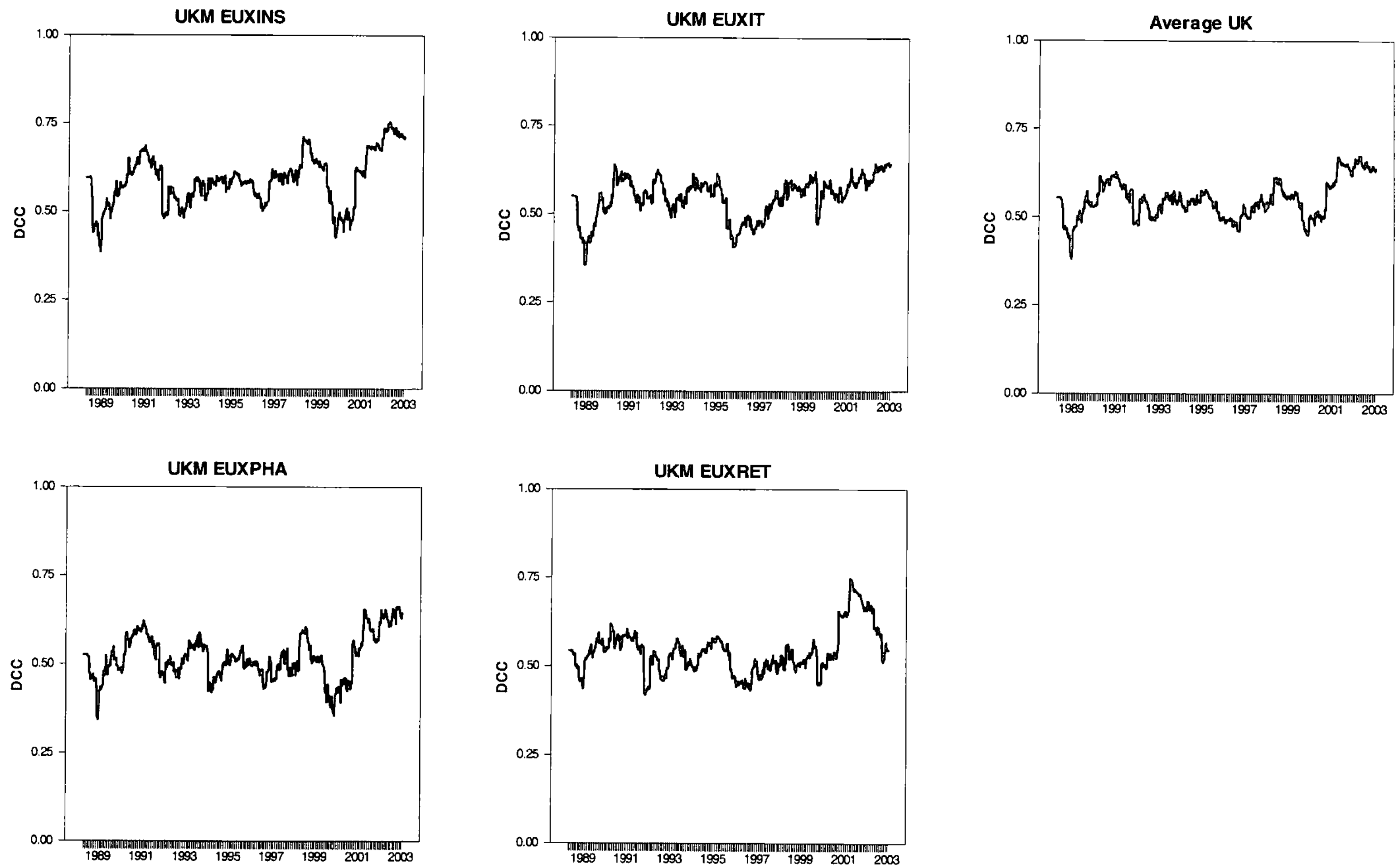
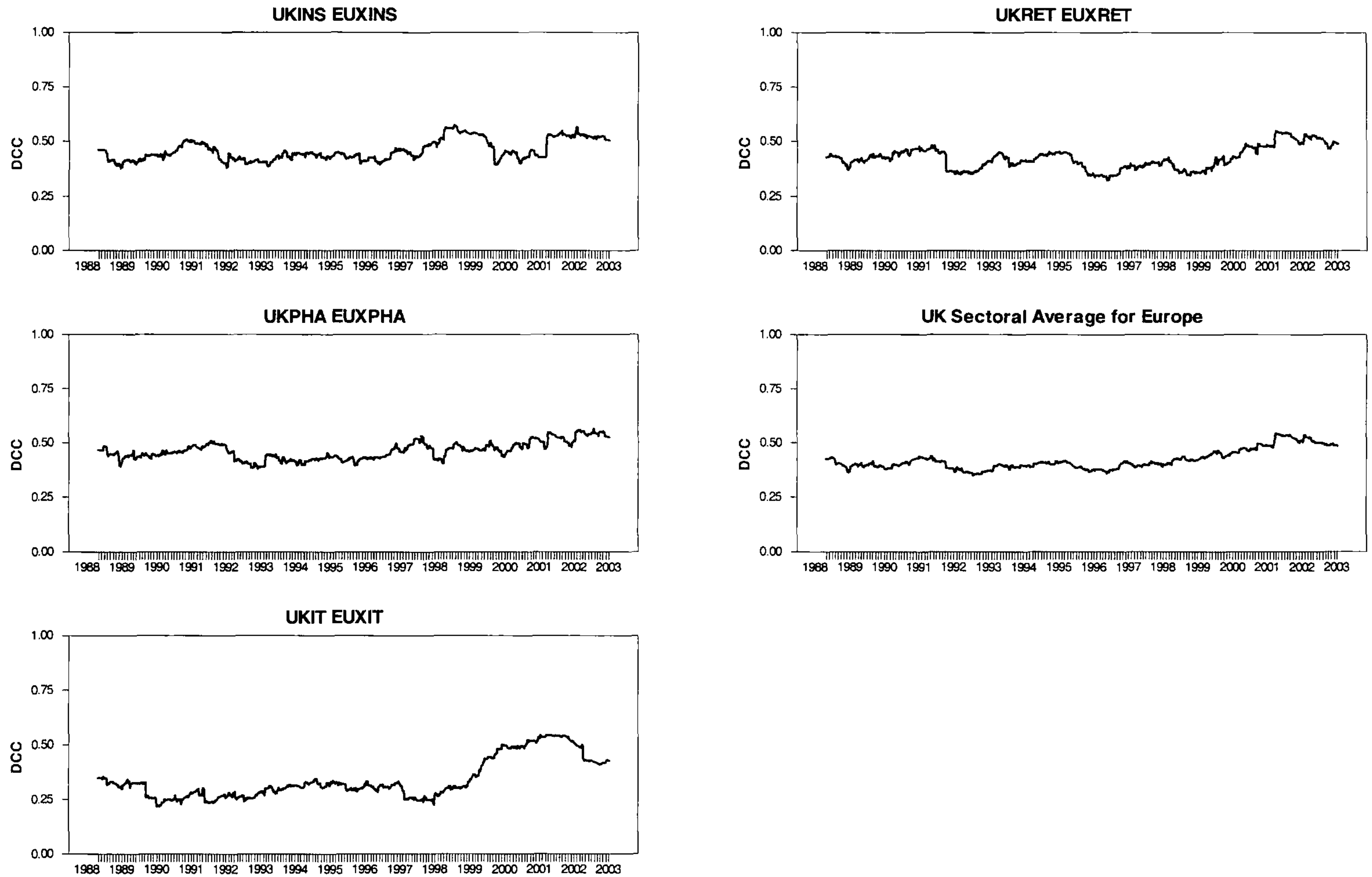


Figure A5.14 DCC time-varying correlations between the UK sectoral stock markets and European sectoral stock markets



APPENDIX 5.1b

Summary of BEKK-type MVGARCH model estimated

Volatility Transmission model for between US sectoral stock markets and the UK stock market.

Variables	MVGARCH MODEL	CONVERGENCE
USINS and UKM	BEKK(1,1)	YES
USPHA and UKM	BEKK(1,1)	YES
USIT and UKM	BEKK(1,1)	YES
USRET and UKM	BEKK(1,1)	YES
USM and UKM	BEKK(1,1)	NO
USM and UKM	Vector Diagonal Model	YES

Volatility Transmission model for between European sectoral stock markets and the UK stock market.

Variables	MVGARCH MODEL	CONVERGENCE
EUINS and UKM	BEKK(1,1)	NO
EUPHA and UKM	BEKK(1,1)	NO
EUIT and UKM	BEKK(1,1)	NO
EURET and UKM	BEKK(1,1)	YES
EUM and UKM	BEKK(1,1)	YES
EUINS and UKM	Vector Diagonal Model	YES
EUPHA and UKM	Vector Diagonal Model	YES
EUIT and UKM	Vector Diagonal Model	YES

Three-variable volatility transmission model for the US, European and UK stock markets

Variables	MVGARCH MODEL	CONVERGENCE
USINS, EUINS and UKMKT	BEKK(1,1)	NO
USPHA, EUPHA and UKMKT	BEKK(1,1)	NO
USIT, EUIT and UKMKT	BEKK(1,1)	NO
USRET, EURET and UKMKT	BEKK(1,1)	NO
USM, EUM and UKM	BEKK(1,1)	NO
USINS, EUINS and UKMKT	Vector Diagonal Model	YES
USPHA, EUPHA and UKMKT	Vector Diagonal Model	YES
USIT, EUIT and UKMKT	Vector Diagonal Model	YES
USRET, EURET and UKMKT	Vector Diagonal Model	YES
USM, EUM and UKM	Vector Diagonal Model	YES

Inter-sectoral volatility transmission between US sectoral stock markets and UK sectoral stock markets.

Variables	MVGARCH MODEL	CONVERGENCE
USINS and UKINS	BEKK(1,1)	NO
USPHA and UKPHA	BEKK(1,1)	YES
USIT and UKIT	BEKK(1,1)	NO
USRET and UKRET	BEKK(1,1)	NO
USINS and UKINS	Vector Diagonal Model	YES
USIT and UKIT	Vector Diagonal Model	YES
USRET and UKRET	Vector Diagonal Model	YES

Inter-sectoral volatility transmission between European sectoral stock markets and UK sectoral stock markets.

Variables	MVGARCH MODEL	CONVERGENCE
EUINS and UKINS	BEKK(1,1)	NO
EUPHA and UKPHA	BEKK(1,1)	NO
EUIT and UKIT	BEKK(1,1)	YES
EURET and UKRET	BEKK(1,1)	NO
EUINS and UKINS	Vector Diagonal Model	YES
EUPHA and UKPHA	Vector Diagonal Model	YES
EURET and UKRET	Vector Diagonal Model	YES

Three-variable inter-sectoral volatility transmission model for the US, European and UK sectoral stock markets

Variables	MVGARCH MODEL	CONVERGENCE
USINS, EUINS and UKINS	BEKK(1,1)	NO
USPHA, EUPHA and UKPHA	BEKK(1,1)	NO
USIT, EUIT and UKIT	BEKK(1,1)	NO
USRET, EURET and UKRET	BEKK(1,1)	NO
USINS, EUINS and UKINS	Vector Diagonal Model	YES
USPHA, EUPHA and UKPHA	Vector Diagonal Model	YES
USIT, EUIT and UKIT	Vector Diagonal Model	YES
USRET, EURET and UKRET	Vector Diagonal Model	YES

APPENDIX 5.1c

Examples of a complete estimation results for MVGARCH models estimated.

BEKK model for US Insurance sector against the UK stock market

```
usins.ukm.bekk <- mgarch(usins.ukm ~ 1,  ~ bekk(1, 1))
Iteration  15  Step Size = 0.0733537  Likelihood =  3721.09

R-Square = 0.0000988052 is less than tolerance = 0.0001
Convergence reached.

Call: mgarch(formula.mean = usins.ukm ~ 1, formula.var =  ~ bekk(1, 1))

Mean Equation: usins.ukm ~ 1

Conditional Variance Equation:  ~ bekk(1, 1)

Conditional Distribution:  gaussian

--------------------------------------------------------------

Estimated Coefficients:
--------------------------------------------------------------
                    Value Std.Error t value   Pr(>|t|)
          C(1)  0.003234 0.0007916   4.086 2.431e-005
          C(2)  0.002514 0.0007875   3.192 7.349e-004
       A(1, 1)  0.006671 0.0010101   6.604 3.744e-011
       A(2, 1)  0.004258 0.0015240   2.794 2.671e-003
       A(2, 2)  0.001693 0.0014565   1.163 1.227e-001
 ARCH(1; 1, 1)  0.380051 0.0401818   9.458 0.000e+000
 ARCH(1; 2, 1)  0.074760 0.0296371   2.523 5.927e-003
 ARCH(1; 1, 2)  0.109763 0.0316252   3.471 2.741e-004
 ARCH(1; 2, 2)  0.186474 0.0257905   7.230 5.878e-013
GARCH(1; 1, 1)  0.879030 0.0199804  43.995 0.000e+000
GARCH(1; 2, 1) -0.045885 0.0126528  -3.626 1.532e-004
GARCH(1; 1, 2) -0.029545 0.0247618  -1.193 1.166e-001
GARCH(1; 2, 2)  0.970330 0.0119462  81.225 0.000e+000

--------------------------------------------------------------

AIC(13) = -7416.175
BIC(13) = -7355.823

Normality Test:
--------------------------------------------------------------
      Jarque-Bera   P-value Shapiro-Wilk P-value
usins       26.68 1.61e-006       0.9904  0.9546
  ukm       80.08 0.00e+000       0.9916  0.9848

Ljung-Box test for standardized residuals:
--------------------------------------------------------------
      Statistic P-value Chi^2-d.f.
usins    19.696 0.07306         12
  ukm     9.198 0.68596         12

Ljung-Box test for squared standardized residuals:
--------------------------------------------------------------
      Statistic P-value Chi^2-d.f.
usins     11.13  0.5177         12
  ukm     15.96  0.1931         12

Lagrange multiplier test:
--------------------------------------------------------------
       Lag 1   Lag 2   Lag 3   Lag 4   Lag 5  Lag 6   Lag 7
usins 0.9185  0.2647 -1.2260  1.1836 -1.6027 0.2020 -0.1146
  ukm 3.2920 -0.9811 -0.1493 -0.4828 -0.5082 0.9622  0.1800
```

	Lag 8	Lag 9	Lag 10	Lag 11	Lag 12	C
usins	0.4998	-0.4902	-1.13821	1.191	0.14216	0.9573
ukm	-1.4468	0.1017	0.01952	-1.016	0.07906	-0.3659

	TR^2	P-value	F-stat	P-value
usins	10.69	0.5559	0.9855	0.5689
ukm	16.03	0.1900	1.4887	0.2339

BEKK model for Europe retail sector against the UK stock market

```
> exret.ukm.bekk <- mgarch(exret.ukm ~ 1,  ~ bekk(1, 1))
Iteration  22  Step Size = 0.0615429  Likelihood =  3755.69

R-Square = 0.00009851351 is less than tolerance = 0.0001
Convergence reached.

> summary(exret.ukm.bekk)

Call: mgarch(formula.mean = exret.ukm ~ 1, formula.var =  ~ bekk(1, 1))

Mean Equation: exret.ukm ~ 1

Conditional Variance Equation:  ~ bekk(1, 1)

Conditional Distribution:  gaussian

--------------------------------------------------------------

Estimated Coefficients:
--------------------------------------------------------------
                    Value Std.Error   t value   Pr(>|t|)
          C(1)  0.002848 0.0008483   3.35700 4.135e-004
          C(2)  0.002457 0.0007648   3.21239 6.859e-004
       A(1, 1)  0.002917 0.0075184   0.38797 3.491e-001
       A(2, 1)  0.010157 0.0213984   0.47466 3.176e-001
       A(2, 2)  0.004142 0.0496570   0.08341 4.668e-001
 ARCH(1; 1, 1)  0.210721 0.0566741   3.71812 1.077e-004
 ARCH(1; 2, 1)  0.316798 0.0385201   8.22423 4.441e-016
 ARCH(1; 1, 2)  0.210618 0.0644931   3.26574 5.703e-004
 ARCH(1; 2, 2) -0.125582 0.0541895  -2.31746 1.037e-002
GARCH(1; 1, 1)  0.782954 0.0350614  22.33093 0.000e+000
GARCH(1; 2, 1) -0.162557 0.0451148  -3.60319 1.674e-004
GARCH(1; 1, 2)  0.276561 0.0779520   3.54784 2.061e-004
GARCH(1; 2, 2)  0.895126 0.0698634  12.81250 0.000e+000

--------------------------------------------------------------

AIC(13) = -7485.382
BIC(13) = -7425.03

Normality Test:
--------------------------------------------------------------
     Jarque-Bera    P-value Shapiro-Wilk P-value
exre       43.22 4.110e-010       0.9867  0.6070
 ukm       19.75 5.149e-005       0.9871  0.6686

Ljung-Box test for standardized residuals:
--------------------------------------------------------------
     Statistic P-value Chi^2-d.f.
exre     7.575  0.8174         12
 ukm    16.692  0.1615         12

Ljung-Box test for squared standardized residuals:
--------------------------------------------------------------
     Statistic P-value Chi^2-d.f.
exre    12.223  0.4279         12
 ukm     7.242  0.8412         12
```

```
Lagrange multiplier test:
--------------------------------------------------------------

      Lag 1   Lag 2   Lag 3   Lag 4   Lag 5 Lag 6   Lag 7  Lag 8  Lag 9  Lag 10
exre 1.1307  0.9064 -1.6488 -0.9481 -0.6259 0.332 -0.5779 -1.465 0.8060  1.7233
 ukm 0.7759 -0.2381  0.3216 -0.1026 -1.7577 1.243  0.3043 -1.140 0.8704 -0.3353

       Lag 11  Lag 12      C
exre  0.05261 0.14743 0.4251
 ukm -0.54948 0.09578 0.8350

       TR^2 P-value F-stat P-value
exre 12.197  0.4300 1.1271  0.4475
 ukm  7.878  0.7946 0.7238  0.8237
```

Vector diagonal vec model for the Europe stock index sector against the UK stock market

```
> eurxm.ukm.vdvec <- mgarch(eurxm.ukm ~ 1,  ~ dvec.vec.vec(1, 1))

Iteration   3  Step Size =  1.42896  Likelihood =  4027.45

R-Square = 0.00007579654 is less than tolerance = 0.0001
Convergence reached.

> summary(eurxm.ukm.vdvec)

Call: mgarch(formula.mean = eurxm.ukm ~ 1, formula.var =  ~ dvec.vec.vec(1, 1))

Mean Equation: eurxm.ukm ~ 1

Conditional Variance Equation:  ~ dvec.vec.vec(1, 1)

Conditional Distribution:  gaussian

--------------------------------------------------------------

Estimated Coefficients:
--------------------------------------------------------------
                Value Std.Error t value   Pr(>|t|)
       C(1) 0.002597 0.0007108   3.653 1.383e-004
       C(2) 0.002229 0.0007454   2.990 1.440e-003
    A(1, 1) 0.007267 0.0008674   8.378 1.110e-016
    A(2, 1) 0.007047 0.0010579   6.661 2.599e-011
    A(2, 2) 0.006657 0.0006792   9.802 0.000e+000
 ARCH(1; 1) 0.342739 0.0276983  12.374 0.000e+000
 ARCH(1; 2) 0.377051 0.0292752  12.880 0.000e+000
GARCH(1; 1) 0.875320 0.0238766  36.660 0.000e+000
GARCH(1; 2) 0.816577 0.0330497  24.708 0.000e+000

--------------------------------------------------------------

AIC(9) = -8036.905
BIC(9) = -7995.123
```

```
Normality Test:
--------------------------------------------------------------
     Jarque-Bera    P-value Shapiro-Wilk P-value
eurx       45.64 1.227e-010       0.9849  0.3294
 ukm      231.25 0.000e+000       0.9896  0.9185

Ljung-Box test for standardized residuals:
--------------------------------------------------------------
     Statistic P-value Chi^2-d.f.
eurx     9.807  0.6329         12
 ukm    15.711  0.2048         12

Ljung-Box test for squared standardized residuals:
--------------------------------------------------------------
     Statistic  P-value Chi^2-d.f.
eurx     32.56 0.001134         12
 ukm     12.51 0.405671         12

Lagrange multiplier test:
--------------------------------------------------------------
      Lag 1   Lag 2   Lag 3   Lag 4   Lag 5 Lag 6    Lag 7  Lag 8   Lag 9 Lag 10
Lag 11
eurx 4.3385  0.6891 -0.9069 -0.1946 -0.8192 1.596 -0.06287 -1.179 -0.1633  3.143
-1.346
 ukm 0.0784 -1.0048  1.2852 -1.4318 -1.2396 1.411 -1.27104 -1.076  1.4468 -1.419
-0.484

      Lag 12       C
eurx 0.14759 -0.3023
 ukm 0.01477  0.4645

      TR^2  P-value F-stat P-value
eurx 33.27 0.000879  3.164 0.01745
 ukm 13.86 0.309925  1.283 0.33886
```

APPENDIX 5.2

The link between volatility and correlation

Probability theory suggests that when movements of random variables are more volatile, sampling correlations between these variables should be elevated even if the underlying process generating the variables remains unchanged. A formal proof of this link is given in Boyer, et al. (1997). Boyer et al provided the following theorem:

Theorem: Consider a pair of independent and identically distributed (i.i.d.) bivariate random variables x and y with standard deviations σ_x and σ_y, respectively, and covariance σ_{xy}. Let the unconditional correlation between the variables $\rho = \frac{\sigma_{xy}}{\sigma_x \sigma_y}$. The correlation between x and y conditional on an event $x \in A$, for any $A \subset \mathbb{R}$ with $0 < \Pr ob(A) < 1$, is given by:

$$\rho_A = \rho\left[\rho^2 + \left(1-\rho^2\right)\frac{\sigma_x^2}{Var\left(x \middle| x \in A\right)}\right]^{-\frac{1}{2}} \qquad \textbf{(A52.1)}$$

Proof: Let u and v be two independent standard normal variables. Now construct two bivariate normal random variables x and y with means μ_x and μ_y, respectively, standard deviations σ_x and σ_y, respectively, and correlation coefficient ρ:

$$x = \mu_x + \sigma_x u \qquad \textbf{(A52.2)}$$

$$y = \mu_y + \rho\sigma_y u + \sqrt{1-\rho^2}\sigma_y v \qquad \textbf{(A52.3)}$$

Consider an event $x \in A$, for any $A \subset \mathbb{R}$ with $0 < \Pr ob(A) < 1$. By definition, the conditional correlation coefficient between x and y, ρ_A is given by:

$$\rho_A = \frac{Cov\left(x, y \middle| x \in A\right)}{\sqrt{Var\left(x \middle| x \in A\right)}\sqrt{Var\left(y \middle| y \in A\right)}} \qquad \textbf{(A52.4)}$$

By substituting for u in (A52.3) using equation (A52.2), then substituting the resulting expression for y into (A52.4), and using the fact that x and v are independent by construction, we can rewrite (A52.4) as:

$$\rho_A = \frac{\left(\rho\sigma_y / \sigma_x\right) Var\left(x \middle| x \in A\right)}{\sqrt{Var\left(x \middle| x \in A\right)}\sqrt{\left(\rho^2\sigma_y^2 / \sigma_x^2\right) Var\left(x \middle| x \in A\right) + \left(1 - \rho^2\right)\sigma_y^2}}$$

(A52.5)

(A52.5), can be simplified to get (A52.1).

Thus, the conditional correlation between x and y is larger (smaller) than ρ in absolute value if the conditional variance of x given $x \in A$ is larger (smaller) than the unconditional variance of x.

This proof is based a property of bivariate normal random variables that each component can be expressed as the weighted average of the other and of an independent variable that is normally distributed (Goldberger (1991)).

APPENDIX 5.3

A Primer on Exponentially Weighted Moving Average (EWMA) Volatility Estimation

This simplified primer introduces the basic foundations of EWMA volatility estimation and provides practical examples of how to compute EWMA volatility, correlations and covariance estimates using Microsoft Excel. It should serve as a toolbox for academics wishing to illustrate how to prepare EWMA historical volatility and EWMA conditional correlation graphs.

Financial market volatility is a measure of the variation in the historical prices of financial assets or the expected variation reflected in prices of traded options on these assets[285]. It is therefore a measure the risk exposure of financial market participants.

Equally weighted moving average volatility

The starting point for measuring historical volatility is to compute the standard deviation of asset returns. If returns are lognormal, the second moment of the lognormal distribution, the variance, captures the variability in log returns. The standard deviation, the standardised variance, is equal to the square root of the variance. The most widely used form of the standard deviation is a rolling n-period equally weighted moving average of the deviations from the average log returns.

Using daily data for example, the equally weighted n-period standard deviation at time T is given as:

[285] This appendix focuses on historical volatility.

$$\sigma_T = \sqrt{\frac{1}{n-1}\sum_{t=T-n}^{T-1}\left(r_t - \bar{r}\right)^2} \qquad \text{(A53.1)}$$

where r_t is the continuously compounded daily log returns – calculated as the log price changes – and $\bar{r}$ is the estimated average continuously compounded return over the n-period.

Alternatively, an n-period equal weighted moving average of past squared returns is used[286]. This is given as:

$$\sigma_t = \sqrt{\frac{1}{n}\sum_{i=0}^{n-1} r_{t-i}^2} \qquad \text{(A53.2)}$$

where r_t is the continuously compounded log return in period t and n is the number of days used to compute the volatility. The estimated standard deviation is multiplied by square root of 252 to convert to annualised volatility. Equally weighted moving average historical volatility for FTSE 100, DAX 30 and CAC40 is given in Figure A53.1.

Volatility estimates generated by (A53.1) or (A53.2) are less accurate when there are large returns or price changes. Forecasts are distorted because each observation is equally weighted in the moving average. The distortion is due to what is known as "ghosting" effects: large changes in asset returns generate huge spikes in volatility during the large return period; but the

[286] This uses the assumption that the mean of returns is equal to zero.

volatility estimate drops dramatically after the large return period. The equally weighted moving average estimate is therefore less robust in capturing the full information about the dynamics of asset returns. To mitigate the effects of these large observations on the moving average estimates of volatility; observations in the return series should be weighted differently. The method of applying exponentially declining weights is a preferred alternative.

Equally weighted rolling window estimation of volatility is also limited because the selection of the window length is arbitrary and different results could be obtained with different windows. Volatility estimated in this way may not be representative of the true underlying process.

Exponentially Weighted Moving Average (EWMA)

EWMA Volatility

The EWMA method of estimating volatility applies the method of exponential smoothing to the data[287]. It uses a smoothing parameter to give more weight to the most recent observations and less weight to older observations in the data. The smoothing process is exponential because the weights employed lie along an exponential curve. Following a shock, EWMA models react more quickly not only to the shock itself, but also to any recovery in the market as the impact of the shock is absorbed. The smoothing parameter, which range between zero and one, measures the persistence of shocks to volatility and therefore captures the 'volatility clustering' phenomenon. A high smoothing parameter indicates that volatility is highly persistent but less reactive whilst a low smoothing parameter suggests that volatility is highly reactive to shocks although the effects of these shocks decays rapidly. In other words, the closer λ is to one, the more weight is given to last period's observation relative to the current periods. The choice of the smoothing parameter is largely subjective and sometimes quite arbitrary; but can also be obtained from an IGARCH model, which is discussed below[288].

The n-period EWMA estimate of the standard deviation at time T is given as[289]:

$$\sigma_T = \sqrt{\frac{1}{\sum_{i=0}^{n-1} \lambda^i} \sum_{t=T-n}^{T-1} \lambda^{T-t-1} r_t^2 \frac{1}{n}} \qquad \text{(A53.3)}$$

where λ, $0<\lambda<1$, is the smoothing parameter that measures the rate of decay or persistence in the series. The length of the memory of the estimate is determined by n. The denominator in (A53.3) converges to $1/(1 - \lambda)$ as $n \to \infty$; in the limit, the EWMA standard deviation estimate collapses to[290]:

---

[287] For a theoretical foundation on exponential smoothing, see for example Abraham and Ledolter (1983), Montgomery, et al. (1990) and Saligari, et al. (1997).

[288] RiskMetrics Group suggest using 0.94 as the smoothing parameter for financial asset prices. See RiskMetrics™ (1996).

[289] The n-period exponentially weighted moving average of a log return time series is defined as: $\dfrac{r_{t-1} + \lambda r_{t-2} + \lambda^2 r_{t-3} + \cdots + \lambda^{n-1} r_{t-n}}{1 + \lambda + \lambda^2 + \cdots + \lambda^{n-1}}$. In the EWMA model the variance is not calculated in mean deviation form. The EWMA variance estimate is equal to one minus the smoothing parameter multiplied by the sum of the squared returns scaled by the smoothing parameter raised to a power (this power is equal to one less than the period of the return). The square root of this, the standard deviation is given in (A53.4).

[290] Technically speaking one does not have to define the length of the memory period, n, because the denominator in (A53.3) converges to $1/(1 - \lambda)$ as $n \to \infty$ and no weight is place on all observations in the past. This is an advantage the EWMA estimation has over the n-period rolling window equally weighted volatility estimate.

$$\sigma_T = \sqrt{(1-\lambda)\sum_{i=1}^{\infty} \lambda^{i-1} r_{T-i}^2} \qquad \text{(A53.4)}$$

In recursive form the model in (A53.4) can be written as:

$$\sigma_t = \sqrt{(1-\lambda) r_{t-1}^2 + \lambda \sigma_{t-1}^2} \qquad \text{(A53.5)}$$

The estimated standard deviation is multiplied by square root of 252 to convert to annualised volatility and multiplied by 100 to convert to percentages. Equally weighted moving average historical volatility for FTSE100, DAX30 and CAC40 is given in Figure A53.1.

The recursive method requires a starting value forλ. The first observations or a subjective average is normally used. The model in (A53.5) is very similar to a GARCH (1, 1) volatility model. EWMA historical volatility for FTSE100, S&P500 and CAC40 is given in Figure A52.2. The relationship between EWMA volatility and GARCH volatility is discussed below.

EWMA Covariance and Correlation estimates

The EWMA covariance and correlation follows naturally from the EWMA variance and standard deviation estimates.

The EWMA covariance between two return series is written as:

$$\sigma_{12,t} = (1-\lambda)\sum_{i=1}^{\infty} \lambda^{i-1} r_{1,t-i} r_{2,t-i} \quad \text{(A53.6)}$$

The EWMA covariance is written in recursive form as:

$$\sigma_{12,t} = (1-\lambda) r_{1,t-1} r_{2,t-1} + \lambda \sigma_{12,t-1} \quad \text{(A53.7)}$$

It straightforward to show that the EWMA correlation is equal to:

$$\rho_{12,t} = \frac{\sigma_{12,t}}{\sigma_{1,t}\sigma_{2,t}} \quad \text{(A53.8)}$$

where the terms in the denominator of (A53.8) are the EWMA standard deviation for each return series and the numerator is the EWMA covariance between the two return series.

The relationship between EWMA volatility and GARCH volatility

EWMA volatility is a special case of GARCH volatility. GARCH volatility models are sophisticated maximum likelihood estimation models that accounts for time-varying volatility. The academic literature suggests that financial market prices are best described by time-varying risk characteristics (see for example, Engle (2001b)) . An example of such time variation in volatility is the volatility clustering pattern reported in financial markets: large volatility movements are more likely to be succeeded by further large volatility movements *of either sign* than by small movements. The EWMA model is equivalent to an Integrated GARCH (IGARCH) model without a constant term. The parameters in the

IGARCH model are restricted to sum to unity[291]. A good way to calculate the smoothing parameter in the EWMA model is to estimate an IGARCH model without a constant and use the GARCH parameter as the smoothing parameter in the EWMA model. The EWMA correlation and covariance are very similar to the covariance and correlation estimates computed using a simple bivariate GARCH or IGARCH model. The EWMA covariance in recursive form is identical to the structure of the expanded covariance term in restricted bivariate GARCH model. The smoothing parameter for the covariance terms can therefore be estimated from a bivariate IGARCH model.

EWMA and bivariate GARCH correlations are generally referred to as conditional correlations. There are a number more powerful GARCH-based models used to compute conditional correlations including, the dynamic conditional correlation GARCH (DCC-GARCH) model suggested by Engle (2002a)[292]. GARCH-based models have a fundamental advantage over n-period equally weighted rolling window estimation because they do not require the arbitrary selection of a window length. Maximum likelihood parameters are estimated instead, which is a more efficient way of dealing time-varying or conditional volatilities. There is also evidence that GARCH models produce more realistic medium-term forecasts than EWMA models because, GARCH volatility and correlation term structure forecasts converge to the long-term average level.

[291] The basic GARCH (1, 1) model, $\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$; nests the EWMA model with restrictions $\alpha_0 = 0$ and $\alpha_1 + \beta = 1$.

Practical Implementation[293]

For the technical user, routines for computing EWMA volatility, correlations and covariance estimates can be easily set up in standard econometric packages such as RATS. For the non-technical user, suggestions for setting up an Excel spreadsheet to compute EWMA volatility estimates are given below. There is however one caveat; the smoothing constant has to be determined subjectively or should be estimated from an IGARCH model without a constant term[294]. To compute n-period EWMA volatility in Excel, it is convenient to rewrite (A52.3) as:

$$\sigma_t = \sqrt{\sum_{i=0}^{n-1} w_i \bullet r_{t-i}^2} \qquad \text{(A53.9)}$$

where w_i, the weights applied to the squared past returns is equal to:

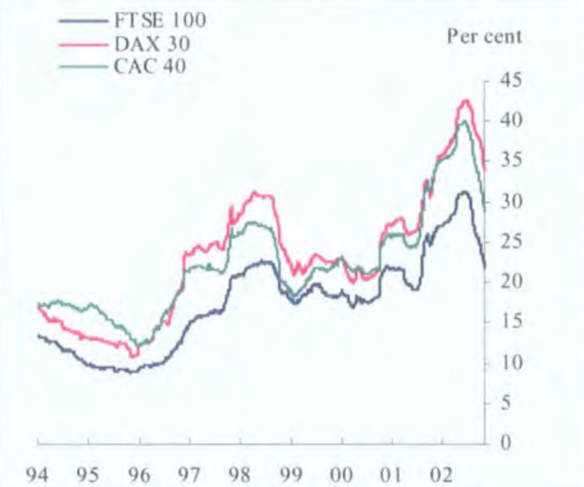
$$w_i = \frac{\lambda^{i-1}}{\sum_{i=0}^{n-1} \lambda^{i-1}} \qquad \text{(A53.10)}$$

Two critical inputs are required to set up the Excel spreadsheet for computing EWMA volatility as given in (A53.9): a column of the calculated weights and a column of the squared asset returns. The square root of the sum of the product of these two columns is the n-period EWMA volatility estimate. This is converted to annualised volatility by multiplying by the square root of 252 and multiplying by 100.

[292] See the discussions on DCC in the main text.
[293] Additional discussions on the practical use of EWMA can be found in Hull (2000) and Alexander (2001).
[294] For covariances, the smoothing parameter would be estimated from a restricted bivariate IGARCH model.

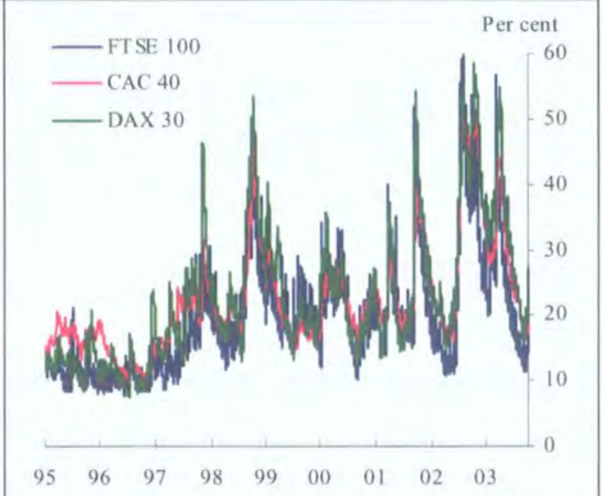
Volatility estimates for the FTSE 100, DAX 30 and CAC 40 is provided in Figure A53.1 and Figure A53.2. The charts illustrate the observed cyclical behaviour of volatility and show various turning points over the last decade. They also show the difference between the equally weighted and EWMA volatility[295].

Figure A53.1: European daily equity index historical volatility[(a)]



(a) Volatility calculated as standard deviation of daily returns over a 252-day rolling window (individual observations equally weighted)

FigureA53.2: European daily equity index historical volatility[(a)]



(a) Volatility calculated as 252-day rolling EWMA

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[295] The smoothing parameters for the EWMA volatility are: FTSE 100, 0.941; DAX 30, 0.925; and CAC40, 0.950. These were estimated from an IGARCH without a constant term.

CHAPTER SIX

CONCLUSIONS

Over the past decade or so, the growing internationalisation of financial markets has led to an explosion of research on capital market integration. The theoretical issues about financial market interlinkages are still being investigated especially as more and more financial services assume a global dimension. The advancement in communication and information technology has greatly facilitated the process of financial globalisation and has led to the removal of visible barriers to investments in domestic financial markets by foreign investors. Despite this rise in financial market interdependence, there is a need for continued assessment of the theoretical and empirical issues surrounding capital market integration. This is important because increased globalisation of financial markets is potentially accompanied by a number of threats to international financial stability. The effects of financial instability will have far reaching consequences for monetary stability and the overall economic health of a nation. This thesis investigates the extent of stock market (financial) and economic integration in Europe.

First, the theoretical foundations of capital market interdependence were assessed in chapter two. It reviews the relevant literature on capital market integration and related issues. The evidence largely suggests that financial market have become more integrated but not perfectly integrated. The evidence comes from the different class of asset price model employed by researches. Multifactor extensions of single factor asset pricing were found to have better in describing the return generating process for international asset returns. The review also indicate that despite the increased integration investors in the developed markets still prefer their domestic markets rather than diversifying internationally. The home bias puzzle still remains. Assessment of the evidence for correlations reveals that the correlation structure of international asset returns is time-varying and that time-varying volatility methods performs reasonably well in describing the transmission mechanisms between different assets and markets. Mixed evidence was obtained about the relationship between capital market integration and real macroeconomic variables.

This chapter could be enhanced by including a number of practical illustrations using empirical examples; especially those that updates or reassess existing stylised facts in the literature. These should then be compared with empirical analysis which uses the latest methodologies that proposed. We intend to pursue this angle very soon.

This thesis also presents new empirical results in three separate empirical chapters. The first essay (chapter three) examines the dynamics of the evolving financial and economic interdependencies between three core European nations (France, Germany and UK) and thirteen other European nations using multiple time series methods suggested by Geweke (1982) in order to capture the time varying nature of capital market integration in Europe. The results suggest that European capital markets are becoming integrated especially since the 1990's. Evidence is found in support of a strong relationship between our time varying integration measures and some macroeconomic variables indicating an increase in economic convergence. Specifically, the result reveals that there are significant co-movements between European stock markets (evidence of financial integration) on the same day rather than across days. This evidence is broadly consistent with international capital market efficiency although we do observe some levels of inefficiency. Results from dynamic panel data analyses suggests the there is reasonable explanatory power in the macroeconomic variables that proxy for the bilateral trade relationship between the pairs of countries investigated. Economic convergence can therefore explain co-movements in financial markets. Financial interdependence must clearly be supported by strong macroeconomic convergence otherwise; speculators in financial markets would succeed in obtaining substantial abnormal returns since the hop from one market to the other. The results have policy implications for both the successful implementation of the euro including maintaining the integrity of the currency and; whether European macroeconomic policy is optimal and efficient when there is greater coordination.

The second essay (chapter four) assesses the comovements in international equity and bond markets. It addresses the question of what extent are international equity and bond markets driven by common shocks and country-specific or idiosyncratic factors. Understanding common asset price behaviour is crucial for international financial and monetary stability. Asset return covariances are key inputs in the construction of portfolios for investors wishing to diversify, which is crucial for international asset allocation decisions. This chapter contributes to this debate by developing a methodology of decomposing the effects of shocks across international equity and bond markets. The dynamic relationship between international equity and bond markets and, the extent of spillovers or contagion between these markets is assessed in a restricted dynamic factor modelling framework. The methodology combines an observable and a latent variable factor structure. The GMM and Kalman filtering decompositions of the restricted factor model of equity and bond returns suggest the following:

- Both equity returns and bond market data suggest that the G10 capital markets can be broadly partitioned into US-Canada and European groups.
- Regional integration is more important for the bond market than for the equity markets as the unobserved EU-regional factor is more pronounced for the bond markets than for the equity markets.
- Substantial idiosyncrasies remain in both markets, which suggest that the markets may not be fully integrated.
- The joint estimation suggests evidence of some spillover effects between the G10 equity markets and G10 long-term bond markets.
- After the introduction of the euro area currency, European equity markets have become more integrated with world equity markets.
- After the introduction of the euro area currency, the unobserved EU-regional factor is no longer important for the euro area countries equity markets but remains important for the euro area long-term benchmark government bond markets
- Substantial idiosyncrasies still remain in the G10 equity and long-term bond markets despite the introduction of the euro are currency. Analysis of the extracted idiosyncratic factor confirms our inference of strong regional integration as opposed universal capital market integration.

On the basis of the above it is clear that despite the increased globalisation in the financial services sector some market segmentation exist meaning that there are still reasonable diversification benefits to be obtained from international portfolio diversification and asset allocation across G10 countries. Investors should focus on those countries with which their domestic markets have very low or negative unobserved idiosyncratic correlation. The results are also important for international financial stability monitoring. Regulators or central bankers involved in macro-prudential assessments would find the aggregate or average estimates reported invaluable indeed; as suggested by Borio (2003).

The third essay (chapter five), addresses the issue of volatility spillovers from international sectoral stock markets in to the UK stock market volatility. Schwert (2002) suggested that the recent episode of high volatility in US stock market is driven by a potential number of factors but perhaps mainly by sectoral volatility, especially volatility in the technology sector. Idiosyncratic volatility or non-market-wide volatility is now regarded as possible explanation of the high stock market volatility that has been observed recently. According to empirical evidence (Campbell, et al. (2001)) aggregate stock markets volatility is mean reverting while firm-level volatility is not. This chapter addresses the issue of idiosyncratic volatility in the UK stock market by examining the effects of international sectoral volatility on UK stock market volatility. It focuses specifically on conditional sectoral volatility spillovers into the UK stock market and assesses the effects of these on overall UK stock market volatility using conditional second moments analysis. The following results were obtained:

- A valid time-varying correlation exits between the selected US and European sectoral markets and, the UK stock market. There is therefore a persistent variation in the correlation structure between these markets
- Average correlations between the selected US sectoral stock markets, the selected European sectoral stock markets and, the UK stock markets have increased over time.
- The Average correlation between the European sectoral markets and the UK stock market is higher than the average correlation between the US sectoral stock market and the UK stock market especially since the mid 1990. A sign of increased capital markets integration between European stock markets and the UK stock market from sectoral point of view.
- There are significant volatility spillovers between the US sectoral stock market and the UK stock market
    - The US pharmaceuticals sector is the most important US sectoral market in terms of their effects on overall UK stock market volatility. Lagged volatility emanating for the US pharmaceuticals sector is found to have the largest impact on UK stock market volatility.
- There are significant volatility spillovers between European sectoral stock markets and the UK stock market.
    - The European IT hardware sector is the sectoral stock market with the greatest impact on UK stock market volatility
- There also exists significant trivariate volatility spillovers between the US, European and the UK stock markets due to number of valid three-variable MVGARCH models estimated.

- In most of these scenarios, the US sectoral stock market volatility is found to have largest impact on UK stock market volatility.

Suggestions for possible extensions of the analysis of this chapter would be to combine the DCC analysis with extreme value copulae analysis to capture the effects of the so-called 'low probability and high impact events' which are mostly missed by standard Gaussian analysis. For example a copula-GARCH model could be fitted for a higher dimension of assets (sectors) to assess joint comovements between these assets.

To conclude, the research exercise conducted in this thesis provides significant contributions to the debate surrounding financial markets integration including, the potential effects for policy issues especially those relating to maintaining international financial stability. The research findings would assist policy makers who work to prevent financial crises occurring. In the unfortunate event of financial crises the results from the empirical chapters and the extensive literature review would be invaluable in formulating strategies for preventing the propagation of financial crises across international financial markets. In addition, the results also have implications for international portfolio diversification. In particular, the fact that G10 equity and bond markets are yet to be fully integrated, despite the anecdotal evidence of increased globalisation, suggests that there are potential diversification benefits for investors diversifying on a country basis across equity and bond markets. Evidence from sectoral volatility spillover analysis also informs on the potential benefits of international diversification since investors could formulate their sectoral diversification strategies, especially the level of exposures in a particular sector, in the light of our empirical evidence on the extent of volatility spillovers between the selected sectors in the countries studied in this thesis. We therefore submit the thesis as a major addition to the exiting theoretical and empirical literature on capital market integration.

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